Addis Ababa University

College of Natural and Computational Sciences

Center for Environmental Science

Prediction of wind energy potential using artificial intelligence and empirical models: A case study in major parts of the Wello highlands, Ethiopia

By: Kefelegn Shewangzaw Afework

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Abstract

Because of the natural fluctuation in wind energy availability between the dry and wet seasons, where hydropower reservoirs experience varying water levels, wind power can serve as a vital supplement to hydroelectric power within Ethiopia's energy framework. Because wind power increases system reliability even during dry seasons, it becomes an essential component of the grid energy mix. This study has focused on predicting wind energy potential in the mountainous Wello highlands region upper basin of Abay and Tekeze of Ethiopia using Artificial Intelligence (AI) and empirical models. Wind speed data from four locations (Wegertena, Lalibela, Amdewak, and Ambamalyam) and eight years data (2013-2020) was used to develop AI and Empirical models for the prediction of wind energy. Long short-term memory (LSTM) neural networks provided the highest accuracy in modeling wind speed, capturing complex seasonal patterns and explaining more than 97% of the variance. On the side of wind power density, all four models at all study sites perform very accurately, scoring above 98.8%, but the gradient boost is the advanced model from the other models at 99.9% only wind power density simulation. The evaluation metrics consistently show that the AI model outperforms the empirical methods on all tasks. LSTM architectures can incorporate long-term weather context, resulting in significantly improved predictions compared to snapshot models that lack native sequence understanding. Accurate wind energy forecasting supports the expansion of renewable infrastructure to sustainably meet Ethiopia's rapidly increasing electricity demand. This study also demonstrates the effectiveness of modern AI in the complex spatiotemporal modeling of wind resources. This provides evidence that deep learning approaches such as LSTM are uniquely positioned to capture diverse wind dynamics based on real-time time series dependency modeling. Accurate wind energy forecasting will be critical as Ethiopia pursues an ambitious sustainable development and decarbonization path over the coming decades. Integrating AI-powered platforms into renewable energy planning and operations will facilitate optimized wind farm site selection and grid integration toward national green energy goals.

Key words: - *AI, ANN, XGBoost, Gradient Boost, LSTM, Wello highlands, wind energy forecasting, and Weibull parameters.*

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LETTER OF CERTIFICATION

This is to Certify that **Kefelegn Shewangzaw Afework** has carried out his thesis on topic "**Prediction of wind energy potential using artificial intelligence and empirical models: A case study in major parts of the Wello highlands, Ethiopia"**. This work is original in nature and sustainable for submission for the awarded degree of master in Center for Environmental Science

Signed by the Examining Committee

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Chairman of the Center for Environmental Science

DECLARATION

I hereby declare that the research entitled "**Prediction of wind energy potential using artificial intelligence and empirical models: A case study in major parts of the Wello highlands, Ethiopia**" is my original work that it has not previously been submitted for any Degree or assessment at any other University, and that all sources I have used or quoted have been indicated and acknowledged by complete reference

Kefelegn Shewangzaw signature: ___________________________

Date: ______________________________

Acknowledgment

I want to start by expressing my sincere gratitude to the almighty God and the holy Virgin Mary for all of their blessings on my life's work. Furthermore, I would like to express my profound gratitude to my supervisors, Dr. Yedilfana Setarge, Dr. Natei Ermias, and Dr. Eyale Bayable, for their professional advice and assistance in finishing my thesis. Their endless patience, never-ending drive, and wealth of experience have given me insightful information. They kindly gave up their valuable time to routinely discuss and go over every part of the task. The current shape of this thesis would not have been possible without their consistent encouragement, patience, and support.

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List of Abbreviation and Acronyms

AI: Artificial Intelligence

ANN: Artificial Neural Network

C=Weibull scale parameter

CDF: Cumulative distribution function

EM: Empirical model

EMI: Ethiopian Meteorological Institute

GWEC: Global Wind energy council

GW: Gigawatt

K: Weibull shape parameter

kW: Kilowatt

LSTM: Long-short term memory

NASA: National Aeronautics and Space Administration

MAE: Mean absolute error

MW: Megawatt

MSE: Mean scared error

PDF: Probability density function

R^2: Coefficient of determination

RNN: Recurrent Neural Network

WS: Wind speed

WPD: Wind power density

V: Average wind speed

XGB: Extreme Gradient Boost

1. Introduction

1.1. Background

Renewable energy sources are gradually replacing fossil fuels due to their low supply, high cost, and negative environmental effects. Because of their practically limitless supply and environmentally benign nature, renewable energy sources like wind, solar, geothermal, hydro, biomass, and ocean thermal energy are garnering support and attention on a global scale.(Muhammad Lawan & Wan Zainal Abidin, 2018). In light of the current market conditions and the global resilience of wind technology, wind energy is likely far more widely accepted today. Numerous studies have been conducted to ascertain the power system's stability and improve wind locations' performance when wind speed availability is the selected factor. Since wind energy is still in its infancy, meeting consumer demand is proving to be difficult for many wind turbine manufacturers. With almost 35 GW of installed capacity, 2014 was actually a record-breaking year for the worldwide wind industry. The ultimate put-in capacity increased by 11% this year to about 318 GW (S. Zhang et al., 2013).

Experts claim that because of wind energy's quick development, most of its potential has not yet been realized, especially in less developed countries. (Abbes & Belhadj, 2014). The main thing impeding the development of green energy in these nations is the lack of reliable data and expertise in identifying and evaluating local wind potential. Furthermore, managers of farms and government representatives are typically non-experts in wind energy. Compared to hydropower, wind power deployment in Africa has been extremely restricted, with only 5.5 GW of installed capacity as of 2018. An estimated 1300 GW of wind energy could power Sub-Saharan Africa, more than tripling the continent's current electricity usage.

In the eastern and northern parts of the continent, the majority of wind resources are found in the vicinity of mountain ranges, coastal areas, and other natural waterways. Top wind energy potential countries include Sudan, Algeria, Egypt, Somalia, and South Africa. The Ethiopia Electric Power Report estimates that the country has a total exploitable wind energy potential of over 1,350 GW. Wind farm development in Ethiopia is still in its infancy, despite the enormous potential of this energy source. Ethiopia lacks a coastline, making it a landlocked nation that may cause wind farm development. But the country experiences a considerable best amount of windiness due to its geographic location, the summer monsoon, tropical Easterlies, and local convergence over the Red Sea. In addition, Tana Lake, the country's northeastern escarpment (cliff), which is close to the regional states of Tigray and Amhara, and the country's eastern highlands, hills, plains, and mountain gaps can all have favorable wind energy conditions and locations. (Tiruye et al., 2021).

The wind speeds in such regions are between 7 and 9 m/s, which is ideal for producing wind energy. Wind regions with a wind density of 300 W/m2 and a wind speed of 6.5 m/s and above are suitable for grid-based energy generation for both technical and economic reasons. East of the country, Ayisha has good potential because its average wind speed is more than 8 m/s. As of right now, the 324 MW total installed capacity of the Ashegoda, Adama I, and Adama II wind farms have been constructed and connected to the grid. Due to the natural cycle of high wind energy availability during the dry season, when hydropower reservoirs are low in water, and low wind energy availability during the wet seasons, when the reservoirs are rapidly filling with water, wind power plays a crucial complementary role with hydroelectric power in the context of Ethiopia's power system. This will increase system reliability even during dry seasons, making wind power an essential component of the grid energy mix.

The Ethiopian government should construct off-grid and micro-grid wind farms to cover remote rural areas and for village-level rural electrification, even though megaprojects are planned to achieve a mix of energy sources. It would also be preferable if micro-grid hybrid solar and wind systems with subsidized tariffs were implemented. Ethiopia has been actively seeking wind energy projects with a September 2021 deadline in order to capitalize on its significant wind resources. Here is a comprehensive overview of wind energy in Ethiopia, covering both installed and uninstalled projects that increase power resilience even during dry seasons.

Though it's always a good idea to examine the most recent sources for the latest details, please be aware that information may have changed since then. Completed Projects: Ashegoda Wind Farm: Located near the town of Ashegoda in the Tigray province, this wind farm is one of Ethiopia's largest. It can produce 120 MW and is composed of 84 wind turbines. Adama I Wind Farm: This 51 MW wind farm is near Adama, a town in Nazret. With 34 wind turbines, it was placed into operation in 2011. Adama II Wind Farm: This wind farm, which has 153 MW in capacity, lies next to Adama. In 2015, with 102 wind turbines, it began to make money. Assela Wind Farm is among the projects that are still being installed. (Biccard, 2020).

Table 1: the existing and upcoming Wind energy plants

Existing Wind Energy Plants	Megawatts (MW)
Adama I	51
Adama II	153
Ashegonda	120
Sub Total	**324**
Under Development wind plant	
Messebo	42
Ayisha	300
DebreBirhan wind park	100
Asela	100
Adama III	150
Sub Total	**692**
Grand Total	**1016**

The upper basins of Tekeze and Abay, as well as the Wello Highlands, are the thesis area. Ethiopia's Wello Highlands are an area in the north of the nation. The region is made up of mountains and highlands that are between 1,500 and 4,620 meters above sea level. The area is renowned for its rough landscape, varied wildlife, and distinctive cultural history. The Wello Highlands region contains the upper basins of the Tekeze and Abay rivers. The Abay River is the primary stem of the Blue Nile, while the Tekeze River is one of the Nile River's principal tributaries. These rivers are significant water sources for domestic use, hydropower production, and agriculture. (Gudina et al., 2021).

Another notable feature of the Wello Highlands region is its potential for the advancement of sustainable energy, particularly wind power. The region is a good choice for wind power projects because of its robust and reliable wind resources. In recent years, the Ethiopian government has been making investments in renewable energy in an attempt to lower carbon emissions and encourage economic development.

The Wello Highlands are a prime illustration of how renewable energy can be used to lessen a community's dependency on fossil fuels while also providing sustainable and reasonably priced electricity. In the Wello Highlands Upper Basin of Tekeze and Abay, wind energy forecast plays a crucial role in the planning and management of wind energy systems. The process of predicting how much energy may be produced in a given location from wind resources requires using a variety of methodologies. For wind turbines to operate as efficiently and optimally as possible, accurate wind energy forecast is essential since it can reduce downtime and increase energy production. (Dingeto Hailu & Kalbessa Kumsa, 2021).

Updating wind energy prediction methods in the Wello Highlands Upper Basin of Tekeze and Abay has been the subject of a recent study. For instance, machine learning algorithms were employed in a study that was published in the journal Renewable Energy in 2021 to forecast the region's potential for wind energy. The study discovered that wind energy potential in the region can be highly accurately predicted using machine learning techniques. (Diriba & Li, 2021).

In 2020, a study was published in the Journal of Energy in Southern Africa, which employed a hybrid model that included fuzzy logic and artificial neural networks to forecast the potential for wind energy in the region. The study discovered that, with a correlation coefficient of 0.92, the hybrid model could correctly forecast the region's potential for wind energy. Additionally, the wind energy potential in the Wello Highlands Upper Basin of Tekeze and Abay was predicted by a 2017 study that was published in the International Journal of Energy and Environmental Engineering using a statistical technique known as the Weibull distribution. According to the study, the Weibull distribution approach had a high degree of accuracy in predicting the area's potential for wind energy.

In the Wello Highlands Upper Basin of Tekeze and Abay, recent studies have shown how important it is to predict wind energy accurately. They also highlight the potential of cutting-edge methods like artificial intelligence and hybrid models to enhance wind energy prediction by utilizing artificial intelligence (AI) algorithms like ANN, XGBoosting, Gradient Boosting, and Long Short-term Memory (LSTM) accuracy. Since the late 1990s, artificial intelligence (AI), or computer systems capable of carrying out activities requiring human intelligence, have advanced significantly. Personalized education, healthcare, smart cities, self-driving cars, fraud detection, logistics, genomics, drug development, finance, criminal justice, agriculture, and environmental sustainability are just a few of the many fields in which it finds extensive use. AI has tripled global investments since 2017, demonstrating its strategic importance. However, given AI's societal ramifications, legislative, ethical, and employment concerns need to be addressed. (Montewka et al., 2020).

1.2. Statement of the problem

Compared to other African nations, Ethiopia grows quickly and has a low rate of urbanization, and it one of the developing nations. In many of the nation's towns, the effects of hydropower provision and on-off (blackout) present significant challenges. The regular blackouts of electricity that occur throughout Ethiopia have turned into a persistent problem.

Regular power outages and exchanges throughout the nation are causing a lot of issues for residents, ranging from home to business facilities. Residents, as well as governmental and private organizations, have been complaining nonstop about how the frequent power outages are interfering with their daily operations (Kebede, 2023). Another issue is accessibility.

An attractive supplier of plentiful energy is necessary for urbanization. Ethiopia is a nation that is increasing quickly, with many businesses, towns, and other infrastructure. However, there is not enough energy to support industrial activity or satisfy the needs of the populace for electrification and other infrastructure. Every year, the nation's growing urbanization and economic development increase the need for energy. This illustrates that power outages (temporary power loss)—occur across the country and that the amount of electricity generated falls short of the amount of power demanded.

In order to tackling the above problem, these thesis emphasis on wind energy availability and validation with high efficiency by identifying the main parameters that boost the wind energy supply at the Wello highland regions where parts of the Tekeze and Abay rivers are emanating from the region.

1.3 Objectives

1.3.1 Main objective

The main objective of this thesis is Prediction of Wind Energy Potential Using Artificial Intelligence and Empirical Models in major parts of the Wello highlands

1.3.2 Specific Objectives

- ✓ To processed the raw data of the chosen parameters. which are taken into account while estimating the site's potential for wind energy.
- ✓ To assess the wind speed at the chosen location by utilizing the AI model at a height of 10 meters and above.
- ✓ To evaluate the forecast and overall efficacy of the artificial intelligence and empirical model in forecasting wind power density at four locations.

1.4 Significance of the Study

This study focused on wind energy forecasting in Ambamariam, Amdework, Wegeltena, and Lalibela using AI and empirical models, which can be used to identify suitable locations for wind farm efficiency design. The study will provide guidance for the future construction of wind farms in the study location. It is anticipated that the study's end product will give relevant details on the state-of-the-art suitability prediction techniques to the relevant parties. The study's conclusions will add to the body of information on the topic and serve as a resource for upcoming researchers who are interested in wind and sustainable energy studies.

1.5 Scope of the study

The analysis of wind speed and wind energy generation on the upper basin rivers of the Abay and Tekeze within the four locations of Ambamaryam, Amdework, Wegeltena, and Lalibea is the primary focus of the thesis. The four locations were chosen due to their excellent and prospective wind speed potentials as well as the availability of enough data to run the performance models. The grid connection study, economic analysis, and wind turbine design are not covered by the prediction results, which only include diagrams and wind energy modeling, estimates of the wind energy potential of the farm sites and seasons, and a comparison of the wind farm potential using artificial intelligence and empirical models based on data from the Ethiopian Meteorological Institute and NASA.

2. Literature Reviews

2.1. Renewable and Fossil fuel energy

The global rapid population growth has leads to a large increase in energy consumption, which is expected to continue growing over time. Energy is vital to humankind in order to promote social and economic progress as well as better human welfare. Energy can be obtained from fossil fuels or renewable energy sources. Because fossil fuel supplies are so scarce and difficult to replace, climate change and global warming are the results. Additionally, they have a lot of negative effects on the environment, such as pollution of the environment during extraction, emissions of greenhouse gases, depletion of resources, and effects on land, water, and wildlife. Because non-renewable resources do not regenerate themselves after consumption, they are not sustainable. (Groth, 2007).

Renewable energy sources, on the other hand, come from nature and may be continuously supplied. It consists of biomass, geothermal energy, the sun, wind, water, and tides in the ocean. (Mohtasham, 2015). Innovations in sustainable energy have significantly reduced the carbon footprint of the electrical industry. The three last applications of renewable energy are transportation, heat, and power. (Jackson et al., 2019). Mostly because wind and solar energy are the alternative energy sources with the greatest rate of growth, the use of electricity has increased dramatically. Many nations have recently begun generating electricity using solar and wind power. However, hydropower accounts for the majority of renewable electricity generation, followed by biofuels. The year-round production of electricity from hydropower is not consistent because of local variables and weather fluctuations. Therefore, it should be supplemented by energy production from other clean sources.

Moreover, since the mid-1970s oil crisis, the generation of energy only from fossil fuels has been shown to be unsustainable. As a result, nations are reducing their dependency on fossil fuels and searching for various alternative energy sources. The main goal of the countries' introduction of alternative energy sources, such wind power, was to lessen their reliance on fossil fuels. The benefits of wind energy for reducing CO2 emissions and protecting the environment are also noteworthy. (Caralis et al., 2008). Since wind farms don't release any pollutants into the sky, they are quickly becoming the perfect source of electricity. Renewable energy sources are becoming more and more popular for reasons other than just being environmentally friendly. Modern energy sources make it easier to generate cash, enhance livelihoods, and support environmental sustainability. (Mithun Mondal et al., 2022).

2.1.1. The role of renewable energy in cities use

Cities have the potential to improve living standards and offer sustainable energy services, given their high rate of energy consumption. Approximately half of the world's population lives in urban areas, and cities are responsible for 70% of carbon emissions connected to energy and 65% of worldwide energy consumption. In order to accommodate the growing needs of the populace and preserve a healthy living environment, city planners and designers must intervene. By utilizing a wealth of renewable energy sources, it may be possible to satisfy these energy demand targets. Due to the fact that renewable energy sources are affordable and sustainable, (Renewable Energy Agency, 2021).

For many cities, energy efficiency is the main priority. On the other hand, a city's sustainable energy system also needs to take advantage of renewable energy sources. In addition to providing a cheap, clean energy source and lowering carbon emissions, renewables also increase economic opportunities in urban areas. (Renewable Energy Agency, 2021).

Pressure variations over the earth's surface brought on by the planet's unequal heating by solar radiation are what generate global wind. The earth's rotation has a significant impact on the atmosphere's circulation, which is a result of the unequal heating of the planet. Seasonal differences in the sun's energy distribution can also contribute to fluctuations in circulation. Since the downward gravitational force typically cancels the pressure gradient force in the vertical direction, this wind responds to horizontal pressure gradients primarily in the horizontal plane. Simultaneously, there exist forces that strive to blend the disparate temperatures and pressures of air masses dispersed throughout the surface of the world. Similar to this, the atmospheric winds are influenced by the air's inertia, the earth's rotation, and friction with the surface of the planet, which causes turbulence.

In addition, variations in time, place, and height above the earth can affect wind speed. These changes in wind speed throughout time fall into four categories: diurnal, yearly, interannual, and short-term. Since inter-annual wind speed variation happens over time scales longer than a year, it can have a significant impact on long-term wind turbine production. A rise in wind speed during the day and a decrease in wind speed from midnight to sunrise is known as diurnal variation. The differential heating of the earth's surface during the daily radiation cycle is the source of this. Diurnal wind fluctuations can vary with location and altitude above sea level, even though daily variations in solar radiation are the cause of these variations in temperate latitudes across relatively flat land areas. Winter typically has the smallest diurnal variations, while spring and summer typically see the biggest. Similarly, the mean variations during time intervals of 10 minutes or less, which include turbulence and gusts, can be used to determine the short-term wind speed variation. (Millstein et al., 2019).

The "urban dimension" is a theory that contends that energy policy and climate change plans need to receive greater focus. Energy consumption and demand are intimately correlated with urbanization and the expansion of megacities. Cities use over 75 percent of the energy produced globally. Thus, producing city-integrated energy may support urban sustainability in the social, environmental, and economic spheres. (Delponte & Schenone, 2020).

The majority of the energy required to run society has come from fossil fuels, with renewable sources accounting for about 15% of global energy sources. Two-thirds of global CO2 emissions are attributed to the energy sector and energy sources, which are the main causes of climate change. In less developed countries like Africa and Asia, 40% of the population lives in cities, whereas in Latin America, a region with high rates of urbanization, 78% of the population lived in urban areas in 2007. Even if fossil fuels continue to be the main source of energy in many cities, there are still significant pollution issues that must be resolved. Despite this, many cities have committed to the renewable energy paradigm. By 2025, Munich and Copenhagen aim to become carbon-neutral cities by sourcing all of their electricity from renewable sources. (Perea-Moreno et al., 2018).

Urban green energy consumption is a way to address the growing need for energy in cities while lowering greenhouse gas emissions and advancing sustainable energy development. An increasing body of research is being done on small-scale wind energy generation. Due to the small wind turbines' cheap maintenance costs, dependability, and minimal environmental impact, installing wind turbines in cities is an easy and environmentally responsible technology. Additionally, it doesn't require the construction of additional electrical infrastructure and operates in low-intensity winds. (Perea-Moreno et al., 2018).

In addition to being crucial for power generation, urban wind energy also helps disperse pollution, improve ventilation, and lessen the impact of the UHI. Urban energy-generating potential is calculated in most nations based on urban wind characteristics. In San Cataldo, urban wind meets 40% of the electricity needs of residential buildings with VAWTs and 33% with VAWTs. Another illustration of an ongoing urban wind project is provided. Three vertically arranged HAWTs in Bahrain provide 11 to 15% of the World Trade Center's electrical energy needs, whereas the two VAWTs installed in Pearl River Tower in Guangzhou, China, only supply 5% of that requirement. (Kammen & Sunter, 2016).

2.1.2 Evolution of wind energy

Energy from wind has been utilized for a very long time. Its use as an energy source dates back thousands of years, to the early days of recorded history. A machine is powered by a wind-driven wheel for the first time in history. Simple windmills were being used in China by the year 1000 AD to pump seawater (source?). The first residence in the world to get electricity was a cottage that was equipped with lighting in 1887, thanks to the first wind turbine ever constructed in Scotland. (Gorigios N., 2021).

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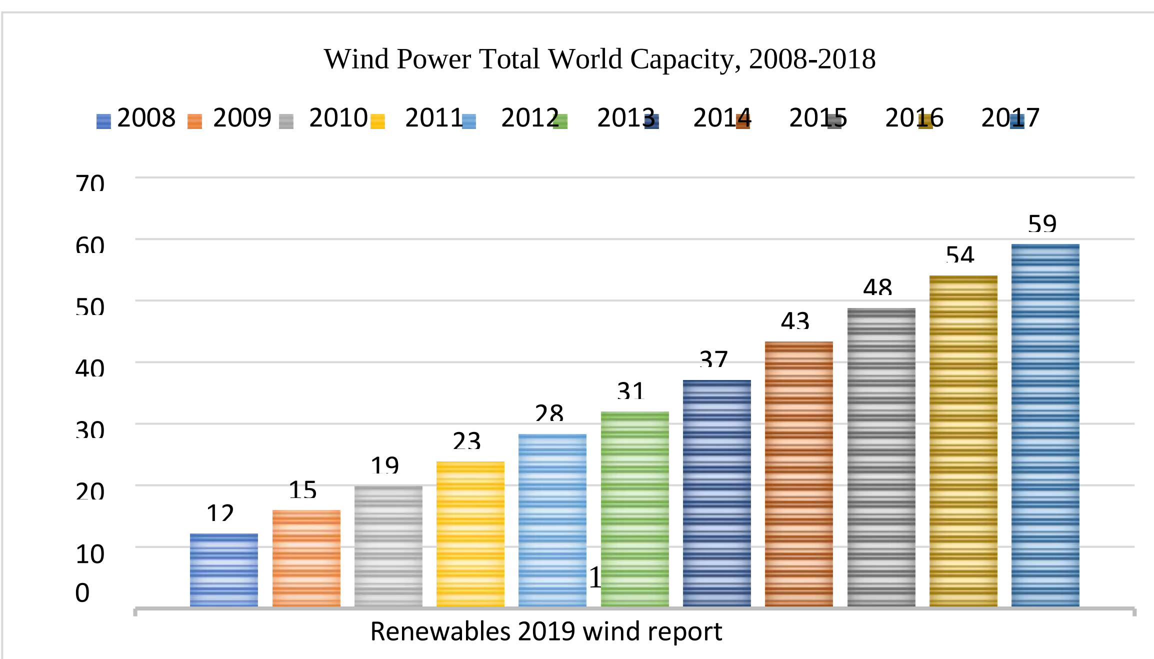


Pollution-free renewable energy sources are a major area of attention for global academics. Wind energy is therefore the most affordable and appropriate energy source. The majority of countries in the world today use wind energy extensively; Figure 2 or 1 displays the top 10 countries' global wind energy capacities. (Mithun Mondal et al., 2022).

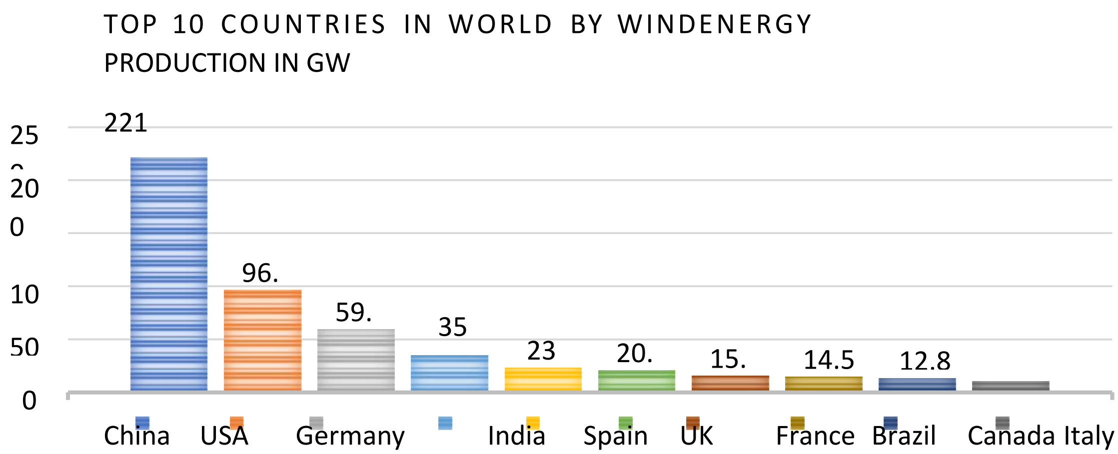


Figure 2: Top ten countries, the cumulative capacities of wind energy (Unwin, 2019)

2.1.3 Wind energy in Africa

On the African continent, renewable energy is expanding steadily. The best is in African nations, which have potential for resources related to wind power. Over 6 GW of installed wind energy is present throughout Africa and the Middle East. 10.7 GW of energy from wind farms is anticipated to be produced in African nations during the next five years. (Wind & Council, 2019).

South Africa leads Africa in wind energy production, having installed 1.17 GW of wind energy so far. By 2030, the country wants to add 8.4 GW of wind energy capacity (see table 1). Morocco and Egypt are Africa's second and third-highest producers of wind energy, respectively. There are presently 870 MW in Morocco, and 50 MW more are being built. Compared to sub-Saharan African nations, where the electrification rate is approximately 95%, Morocco has a high rate. Morocco therefore views the exploitation of renewable resources as a means of assisting the nation in achieving energy independence. Egypt has a great potential for wind resources, especially in the Suez Gulf, where winds average 10.5 m/s. At present, Egypt has constructed approximately 750 megawatts of wind power capacity. They have established a goal of producing 4.3 GW of renewable energy by 2022, of which 2 GW will come from wind energy, which is an essential component of these developments. (Tiyou, 2016).

Ethiopia has erected more than 320 MW of wind energy production capacity, placing it in fourth place. Many people reside in rural locations, and more than 75% of the nation is not connected to the national grid. Ethiopia has enormous energy needs, and producing more electricity would require an annual increase of 20–25%. Kenya is ranked sixth on the continent, and their project, Lake Turkana, is the largest. Although it is not yet finished, it will increase the nation's wind energy capacity from 14 MW to 324 MW (Tiyou, 2016).

Table 2 Top five wind energy capacity countries in Africa

Rank	Countries	Operational (MW)	Under construction (MW)
1	South Africa	1170	840
2	Morocco	870	50
3	Egypt	750	0
4	Ethiopia	324	0
5	Kenya	14	310
	Total	3128	1200

Source: (Tiyou, 2016)

2.1.4 wind energy in Ethiopia

Just 15% of Ethiopians have access to electricity at the moment, with hydropower facilities providing 97% of the country's electricity energy (EEPCO, Ethiopia Electric Power Corporation, 2011). A study conducted by the Ethiopian Electric Power Corporation (EEPCO) found that wind energy and hydropower are complementary because, during the rainy season, hydropower energy is higher and wind energy is lower, respectively (EEPCO, 2006).

Ethiopia offers enormous potential for a variety of renewable energy sources. Above 10 GW are the estimated maximum power that wind energy can produce. This source has the ability to provide long-term energy for Ethiopia's growing local industries as well as for global energy commerce

(Tiruye et al., 2021).

Numerous wind farm projects have been constructed across the nation as of late. The main locations in Ethiopia for wind energy production are Ashegoda (8.5 m/s), Herna (6.9 m/s), and Nazareth (9.3 m/s) (Temesgen, 2011). Wood, oil, coal, and natural gas have been Ethiopia's primary energy sources for millennia. Because of these energy sources' limitations, finite supply, and long-term environmental pollution issues, nations are concentrating on clean and sustainable energy sources. As one of the most affordable renewable energy sources, wind energy is expanding quickly and is becoming more prevalent globally. (Asress et al., 2013).

Ethiopia uses a significant amount of hydropower and has enormous potential for it. But given that climate change can result in decreased precipitation during the dry season, it is imperative to combine a variety of renewable energy sources. Ethiopia is known for having very low levels of both energy consumption and electric power generation in these situations. Fossil fuels are once again used to generate energy during these periods, increasing greenhouse gas emissions and harming the environment. Ethiopia faces challenges meeting its energy needs because of its growing population and economy. Because of the country's strong economic expansion, the need for energy is rising by 10-12% of each year, and only about 14-15% of people have access to power. (Abubakari et al., 2023).

The Aysha II wind farm project can provide 120 MW of electricity in total for Ethiopia. Each of the 48 turbines in the wind farm project has a 2.2 MW generating capacity. Located 700 kilometers east of Addis Ababa in the Somali region of Ethiopia, the Aysha II development got underway in June 2017. At the moment, Ethiopia uses wind energy in a separate region of the nation to produce 324 MW of electricity. These wind farms are Ashegoda Wind Farm, which also generates 120 MW and 153 MW of energy; Adama Wind Farm, which creates 51 MW; and Adama II. The distance between Addis Ababa and the Adama wind farm is 95 kilometers southeast.

Phase I of the Adama wind farm was opened in March 2012, after construction began in June 2011. Following Adama's first phase, EEP and Hydro China inked a second deal for the addition of 153 MW of capacity. In 2015, phase II extra capacity became accessible. The first wind farm in Ethiopia to go online was Adama Wind. (Advisor & Wondie, 2020).

Situated 780 kilometers north of Addis Ababa in the Tigray region, close to Mekelle, the Ashegoda wind farm has 84 wind turbines and can produce 120 MW of electricity. Figure 3 shows the Ethiopian wind farms that are currently in operation.

Figure 2 Operational wind farms in Ethiopia

2.1.5 Artificial Intelligence for Wind Energy

See Artificial Neural Networks (ANN) for further details on the specific AI techniques used in wind energy forecasting: Artificial neural networks (ANNs) are computer models inspired by the structure and functions of the human brain. Artificial neural networks (ANNs) are composed of interconnected nodes, or neurons, arranged in layers of input, hidden, and output layers. In order to forecast wind energy and understand the complex interactions between wind energy output and meteorological factors, artificial neural networks (ANNs) can be trained with historical wind data. Artificial neural networks (ANNs) can forecast results from new input data after training.

XGBoost: A machine learning method that is a member of the ensemble learning family is called Extreme Gradient Boosting. By combining several weak predictive models, or decision trees, it enhances the gradient boosting framework and produces a prediction model that is more accurate and dependable. XGBoost iteratively enhances the performance of the model by minimizing prediction errors through the use of a gradient descent technique. Gradient Boost: Gradient Boosting is an additional ensemble learning method that builds a powerful model by combining several weak predictive models. Models are added to the ensemble one by one(Paiva, 2012).

3. Methodology

3.1 Description of the study area

This thesis was conducted in upper Tekeze and Abay river basins of the Wello Highlands, which is a mountainous region located in northern Ethiopia. The Wello Highlands and its upper basin of the Tekeze and Abay Rivers have been selected for wind energy prediction due to the region's high potential for wind energy development (GWEC,2021). The Wello Highlands are dissected by several river basins. The Tekeze and Abay basins cover most parts of the highlands.

The upper basin of Tekeze river is located in the northwestern part of the Wello Highlands. On the other hand, the Beshilo River is one of the tributaries of the Abay River that originates from the hills of Wello and flows westward into the main Abay River. The upper basin of the Tekeze River is characterized by steep slopes, rugged terrain, and deep valleys. The upper basin of the Abay River is characterized by high plateaus and rugged terrain, with elevations ranging from 1,500 to 4,000 meters above sea level. This makes the wind difference that occurs through geographical positioning crucial for wind energy prediction. That's why these areas were selected for this thesis.

The climate in this region is generally dry, with low rainfall and high temperatures (Edao et al., 2023). According to a study published in the International Journal of Energy and Environmental Engineering, the high altitude and rugged terrain of the Wello Highlands create favorable wind conditions that can be harnessed for electricity generation through wind turbines (Kebede et al., 2006). In addition to the favorable wind conditions, the region's proximity to the national power grid and the growing demand for electricity in in and around the study areas make it an attractive location for wind energy development. According to the Ethiopian government, the country aims to generate 17,300 MW of electricity from renewable sources by 2028, and wind energy is expected to play a significant role in achieving the demand goal (Hameer & Ejigu, 2020).

Overall, the Wello Highlands and its upper basin of the Tekeze and Abay Rivers, especially Wegeltena, Ambamariam, Amdework, and Labella, have been selected for wind energy prediction due to the availability of sufficient data, and favorable wind conditions. The Ethiopian government's policy initiatives and regulatory frameworks are expected to further support the growth of the wind energy sector in the region and contribute to the country's goal of generating electricity from renewable sources.

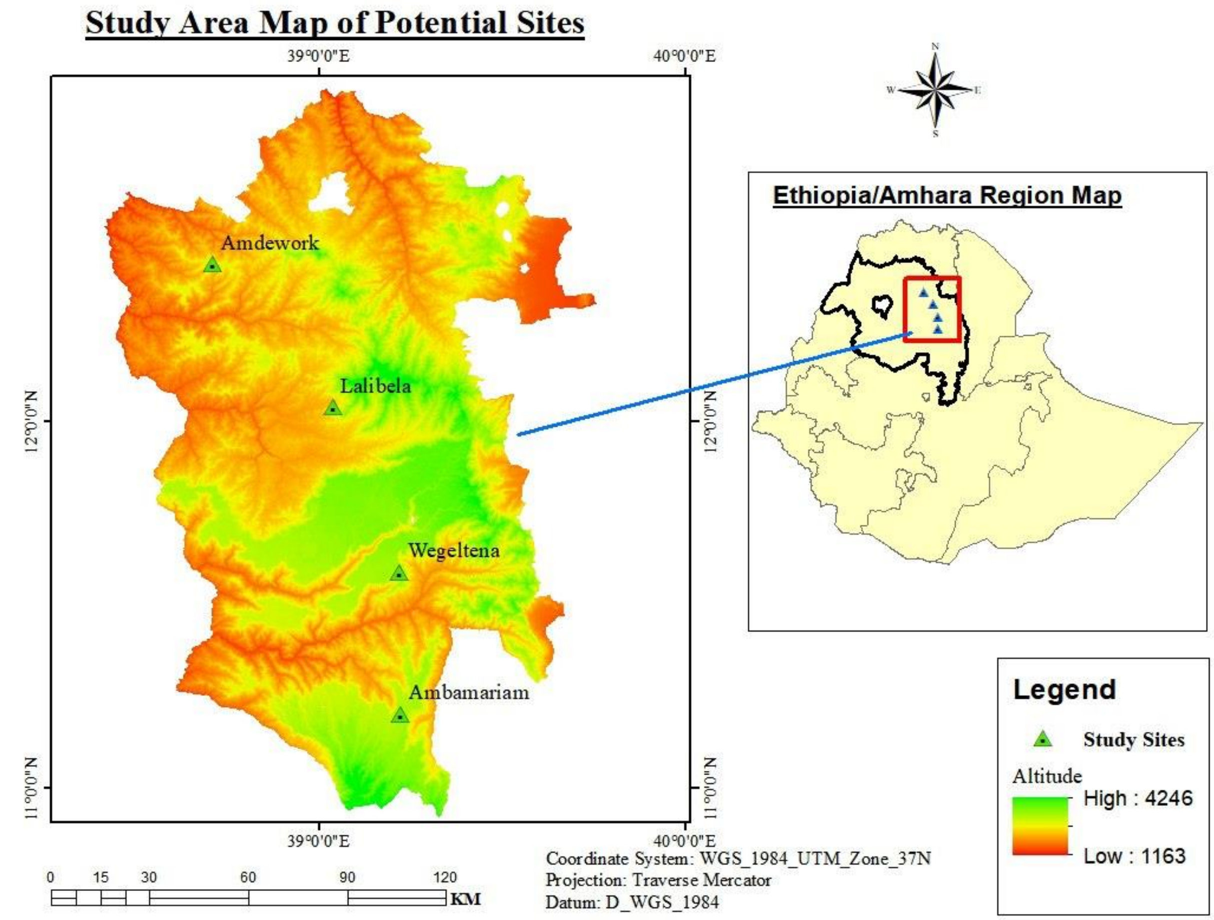
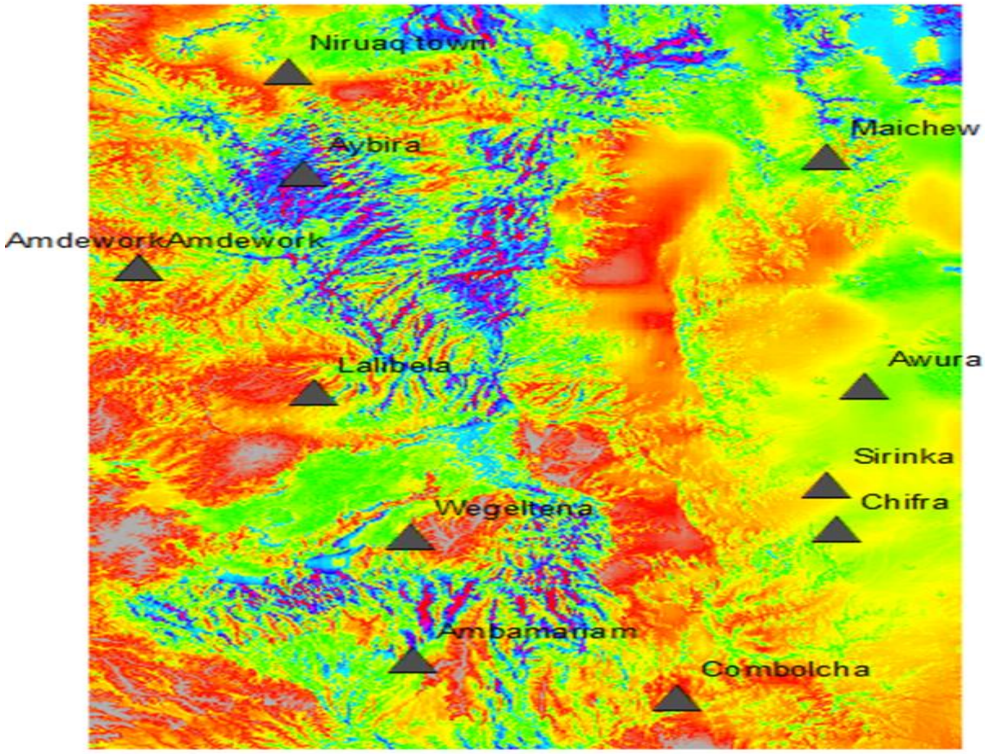


Figure: - 4 Study area maps of Wegeltena, Lalibela, Amdework, and Ambamaryam



The Wind potential of Northern parts of the country according to Global wind atlas report

Table 3: Sources of the data

Pressure	Statistical Data	To calculate wind energy potential	Ethiopian Meteorological Institute (EMI)
Wind Speed	Statistical Data	To calculate wind energy potential	EMI and NASA
Wind direction	Statistical Data	To calculate wind energy potential	EMI and NASA
Temperature	Statistical Data	To calculate wind energy potential	EMI and NASA
Relative humidity	Statistical Data	To calculate wind energy potential	EMI and NASA
Pressure	Statistical Data	To calculate wind energy potential	EMI and NASA
Precipitation	Statistical Data	To calculate wind energy potential	EMI and NASA
Sunshine	Statistical Data	To calculate wind energy potential	EMI and NASA

3.2 Measured average wind speed and Its Extrapolation

The monthly average wind speed v_{av} and the standard deviation σ of the time-series of measured hourly wind speed data would determine using equation (1) and (2), respectively (Eninges Asmare et al, 019):

$$v_{av} = \frac{1}{N}\left(\sum_{i=1}^{N} v_i\right) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

$$\sigma = \left[\frac{1}{N-1}\sum_{i=1}^{N}(v_i - v_m)^2\right]^{1/2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Where Vm **(m/s)** is average wind speed, $\mathbf{v_i}$ **(m/s) i**s daily wind speed, SD is standard deviation and N is the number of measured daily wind speed data.

The artificial neural network wind prediction model gives time series of wind speed values at a given height above ground level (anemometric height). Hence, it is necessary to extrapolate the wind speed time series to other heights, i.e., wind turbine heights (hub height). The conversion can be performed using the power law of Hellman formula (Hadi, 2015).

$$\frac{V}{Vo} = \left(\frac{H}{H_0}\right)^{\alpha} \quad \textbf{----------------3}$$

where v is the wind speed at the necessary altitude. Vo is the wind speed at the reference height H_o. The ground surface friction coefficient, represented α, is between 0.05 and 0.5. Given that all of the stations were situated in or close to towns with potential for trees and shrubs in the surrounding areas, 0.3 was chosen as the friction coefficient (α) of the study area (Hadi, 2015).

3.2.1 Frequency Distribution of Wind Speed

A site's potential for wind energy was ascertained by statistical analysis, which also served to evaluate the site's wind energy output. The geographical location, surface features, and local climate all influence the statistical distribution of wind speeds. The wind speed distribution of a typical site is often described by the Weibull distribution (C. Zhang et al., 2017).

3.2.2 Weibull distribution function of Wind Speed

The distribution functions that are most frequently employed to show wind speed data are the Rayleigh and Weibull functions. A key component in modeling and forecasting wind output and dispersion is the Weibull distribution. The Weibull distribution is incredibly adaptable and simple to use. The two parameters that make up the most basic version of the Weibull distribution are parameter 'c', which has a velocity dimension, and parameter 'k,' also referred to as the scale parameter and dimensionless. The probability density function (PDF) and cumulative distribution function (CDF) of the Weibull distribution can be used to describe it. Probability Density Function (PDF): The Weibull probability density function was utilized by several researchers to model and forecast wind energy. One continuous random variable of the distribution that was employed was

the wind speed. The PDF in mathematical form is: $f(v) = \frac{k}{c} * \left(\frac{v}{c}\right)^{k-1} * exp^{-(v/c)^k}$
(4)

Where c is the Weibull scale parameter whose unit is equal to the wind speed unit, k is the dimensionless Weibull shape parameter, and f (v) is the probability of detecting wind speed v. The wind potential of the study sites is characterized by the Weibull parameters k and c. Finding the frequency with which wind speeds were near a measured speed is made easier by the shape parameter "k." The average wind speed variation in a sample is represented by the value of k; the greater the value of k, the more stable the wind speed. A location's potential for wind is indicated by the scale parameter (c). The considerable wind power is shown by the huge value of "c." Function of Cumulative Distribution (CDF): The likelihood that the wind speed will exceed the value v is provided by the cumulative Weibull distribution F(v), which has the following expression:

$$F(v) = 1 - \exp\left[-\left(\frac{v}{c}\right)^k\right]$$
------------------------------------ (5)

3.2.3 Wind Power Calculation

For any wind stream with speed v (m/s), of cross-sectional area A (m^2), and air density (ρ=1.225$e^{Hp/^{-z}}$ kg/m^3) the theoretical power (P) that is available can be obtained from (Hadi, 2015). Where: -

Z = the elevation of the stations above sea level in meters

HP = the scale height which is equal to 8400 m. Thus, the wind power density calculated based on this formula. $P = \frac{1}{2}\rho A v^3 \quad (Watts)$

(12)

The total wind power density, P/A is the total available power per unit area, which is given by

$$\frac{P}{A} = \left(\frac{1}{2}\rho\frac{1}{n}\sum v_i^3\right) \qquad (13)$$

Where: n is the number of days in a month. Before calculating the average wind power density, v_i^3 of each day for the extrapolated height at 50 m was calculated and the values are summed $\left(\sum v_i^3\right)$, and then divided by the number of days in a month $\frac{1}{n}\left(\sum v_i^3\right)\frac{1}{n}(\sum V_i^3)$.

Weibull parameter

A number of techniques have been developed to calculate the Weibull parameter. The graphic method, moment method, standard deviation method, maximum probability method, energy pattern factor method, and power density approach are a few of these techniques. The standard deviation approach was employed in this work to determine the Weibull parameters. This method is used to determine k and c, respectively, as Ouammi et al. (2010)

For the Weibull distribution, the parameters c and k are related to the mean ($\bar{v}$) and standard deviation (SD) as follows: $C = (\bar{v}\,\Gamma\ (1+1k)\ (1/k)$

$$\mathbf{SD} = \mathbf{c}\sqrt{\left[\boldsymbol{\Gamma}\left(\mathbf{1} + \frac{\mathbf{2}}{\mathbf{k}}\right) - \boldsymbol{\Gamma}^2\left(\mathbf{1} + \frac{\mathbf{1}}{\mathbf{k}}\right)\right]} \tag{14}$$

Where Γ is the gamma function.

We can substitute the given values for $\bar{v}$ and SD into these equations and solve numerically to find k and c.

3.3 Artificial Intelligence Algorithms (Models)

Artificial intelligence (AI) algorithms like artificial neural networks (ANN), XGBoost, gradient boosting, and long short-term memory (LSTM) are playing an increasingly important role in research across many fields, which also implemented in this thesis and they are very popular in current world. AI offers numerous advantages over alternative modeling methods in various research domains:

- **Accuracy**: AI models like deep neural networks are able to capture complex nonlinear relationships and high-order interactions between variables that more traditional models like linear or logistic regression cannot (Belanger & McCallum, 2015). This allows AI to maximize predictive accuracy.

- **Personalization Machine learning algorithms**: have the ability to optimize predictive models for individual subjects, delivering more personalized insights. For instance, AI facilitates precision medicine and tailoring education or interventions to individuals (Johnson et al., 2018).
- **Pattern Recognition Advanced**: AI techniques have the capacity to identify signals and patterns in large, high-dimensional datasets that humans simply cannot perceive (Duan et al., 2016).
- **Automation**: AI can automate lengthy tasks involved in research to increase efficiency. For example, neural networks can simulate complex protein folding mechanisms and reactions drastically faster than conventional simulations (Avery et al., 2022).
- **Handling Missing Data**: Deep learning algorithms have built-in procedures to infer and impute missing values accurately to minimize data loss. This ability increases statistical power for drawing valid inferences from the data (L. Zhang et al., 2021).

3.3.1 XGBoost

XGBoost, short for extreme Gradient Boosting, is a highly efficient and scalable implementation of the gradient boosting algorithm. Developed by Tianqi Chen, it has become one of the most popular and widely used machine learning libraries in both academia and industry. XGBoost is known for its speed, accuracy, and versatility, making it suitable for a wide range of machine learning tasks, including classification, regression, and ranking problems (Chen & Guestrin, 2016).

3.3.2 Gradient boosting machines

Gradient Boosting Machines (GBM) are a class of machine learning algorithms that combine the principles of boosting with gradient descent optimization to produce powerful predictive models. GBMs build an ensemble of weak learners, typically decision trees, sequentially, with each subsequent tree aiming to correct the errors of the previous ones. By iteratively minimizing a predefined loss function, GBMs create a strong predictive model capable of handling complex relationships in the data. GBM algorithms, such as XGBoost, LightGBM, and CatBoost, have gained widespread popularity due to their robustness, scalability, and effectiveness across various domains, including classification, regression, and ranking tasks (Guldberg, 2023)

3.3.3 Artificial Neural Networks:

ANNs are powerful machine-learning algorithm that could predicted wind energy potential in Ethiopia. This algorithm works by simulating the behavior of the human brain, where a network of interconnected neurons learns to recognize patterns in the data. ANNs have several advantages that make them suitable for wind energy prediction. Firstly, they can model complex nonlinear relationships between variables. Secondly, they can handle missing data without losing accuracy. Thirdly, they can handle both numerical and categorical data. Finally, they can learn from large datasets, making them suitable for applications with large amounts of data (Sibi et al., 2013).

3.3.4 Long short-term memory

A particular kind of recurrent neural network called an LSTM network has the capacity to retain context information, making it ideal for learning long-term dependencies. For modeling sequence data, such as text, time series, gene sequences, etc., this makes them incredibly valuable. LSTMs improve the predicted accuracy in a variety of applications, including text production, voice recognition, language translation, and the identification of anomalies in study data (Sundermeyer et al., 2015).

3.4 Methodology: Procedures

3.4.1 Data Collection:

The first step was to collected wind speed, wind direction, precipitation, pressure, sunshine hours, temperature and relative humidity from National Meteorological Institute (NMI).

3.4.2 Data Preprocessing:

The next step would be to preprocess the collected data. It involves cleaning the data, identifying and handling missing data, and converting the data into a suitable format for analysis. The data were check with outliers and anomalies (abnormalities) and would be removed or corrected as needed.

3.4.3 Feature Selection:

Once the data is preprocessed, the next step was to select the features that are most relevant for predicting wind energy potential. The selected features included wind speed, wind direction, temperature, pressure, precipitation, sunshine hour and humidity. These features were used to train the machine learning models.

3.4.4 Model Training and Evaluation:

Once the machine learning and deep learning models have been selected, they were trained and evaluated using the preprocessed data. The evaluation of the models done using different performance metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Coefficient of Determination (R-squared).

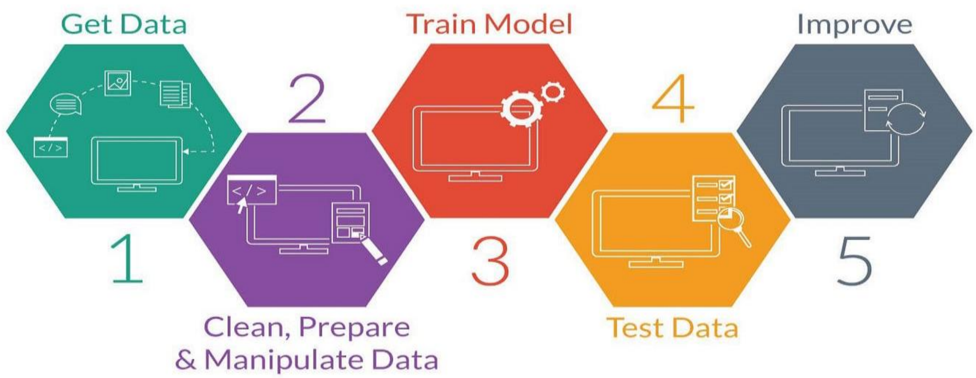


Figure 3 the diagram of work flow for the proposed AI of ANN, XGBoost, Gradient Boosting, and LSTM Models

3.4.5. Empirical Model Development:

In addition to the AI models, empirical models were also developed to predict wind energy potential. These models were developed using the statistical relationships between wind speed and direction, temperature, pressure, and humidity. The empirical models would be compared to AI models to determine which model performs better**.**

3.4.6. Performance Test

The performance of the suggested AI algorithm and the Weibull approaches is assessed using a wide range of parameters. In this case, statistical measures such as the coefficient of correlation (r), mean absolute error (MAE), and root mean square error (RMSE) were applied. (Gaddada and

Kumar, 2015; Natei Ermias Benti et al., 2017; Tegenu Argaw and Eninges Asmare, 2019). The ideal outcome is when these statistics are closer to zero, but for better modeling, the coefficient of correlation, or r, should approach one as nearly as feasible (Table 3).

Table 4: A summary of statistical parameters RMSE, MBE and MPE for the evaluation of the model performance

Statistical	**Mathematical expression in terms of measured and calculated results**	**Preferable Value**
Root mean square error (RMSE)	$\mathrm{RMSE} = \left(\frac{1}{n}\sum_{1}^{n}[y_i - x_i]^2\right)^{\frac{1}{2}}$	Close to zero
Mean bias error (MBE)	$\mathrm{MBE} = \frac{1}{n}\sum_{1}^{n}[x_i - y_i]$	Close to zero
Mean percentage error (MPE)	$\mathrm{MPE}(\%) = \frac{1}{n}\sum_{1}^{n}\left(\frac{[x_i - y_i]}{y_i}\right) * 100$	Between−10% and +10% .
Correlation coefficient (r)	$r = \frac{\sum_1^n[x_i - \bar{x}_i] * [y_i - \bar{y}_i]}{\sqrt{(\sum_1^n[x_i - \bar{x}_i])^2 * (\sum_1^n[y_i - \bar{y}_i])^2}}$	High r (r →1)

Where, **n** is the number of wind speed observations, $\mathbf{y_i}$ is the frequency of observations in wind speed interval i, and $\mathbf{x_i}$ is the Weibull-parameters-based calculated value.

3.4.7 Model Comparison and Selection:

The final step was to compared the performance of the different AI models and empirical models and select the best model for predicting wind energy potential in the desired site.

4. Results and Discussion

In this research work, we concentrated on wind prediction in the upper basin of Abay and Tekeze, Ethiopia's Wello Highlands, using artificial intelligence and empirical models. The study's conclusions show how well-suited it is to forecast wind patterns in these particular areas by using empirical models and cutting-edge AI approaches. Through the integration of advanced algorithms and historical data, the models achieved a considerable improvement in wind prediction accuracy.

The study findings show that applying artificial intelligence and empirical models to wind forecasting significantly increases its accuracy. The planning of wind energy projects, energy generation optimization, and strategic decision-making concerning sustainable energy practices in the region would greatly benefit from these improved forecasts. This study highlights how cutting-edge technologies can improve wind prediction accuracy and dependability, which would ultimately lead to a more efficient and sustainable energy production landscape in Ethiopia's upper basin of the Wello Highlands of Abay and Tekeze.

4.1 Wind energy resource data analysis

This section concise, hourly wind speed, monthly average wind speed, extrapolated wind speed, extrapolated wind power density, wind speed Weibull distribution analysis, and wind power calculations. Monthly average wind speed is the average wind speed computed over a month, whereas hourly wind speed is the wind speed measured every hour. The process of estimating wind speed using the power law at a height other than the recorded height is known as extrapolated wind speed. The process of estimating wind power density using the Weibull distribution function at a height different from the measured height is known as extrapolated wind power density.

Using the Weibull distribution function, wind speed Weibull distribution analysis is a statistical technique for analyzing wind speed data and estimating wind power potential. The Weibull distribution function is used to estimate wind power density and energy density, and wind speed is extrapolated to the hub height of a wind turbine in order to calculate wind power. These ideas are frequently applied in wind energy studies to evaluate a site's suitability for producing wind energy. When estimating the statistical distribution parameters of wind speed data and evaluating a site's potential for wind energy harnessing, the Weibull distribution function is frequently utilized.

4.1.1 Hourly average wind speed at 10 m

Figure 5 illustrates the average hourly variations in wind speeds observed across four distinct sites. The highest wind speed is observed at Site Lalibela, peaking at 18:00 AM with an average speed of 3.78 m/s This peak is likely due to specific atmospheric conditions or geographical features surrounding Site Lalibela, such as local topography or prevailing wind patterns, whereas the lowest wind speed is observed at site Wegeltena, falling at 6:00 AM with an average wind speed of 1.76 m/s. This falling is likely due to specific atmospheric conditions or geographical features surrounding Stie Wegeltena, such as local topography or weather change wind patterns.

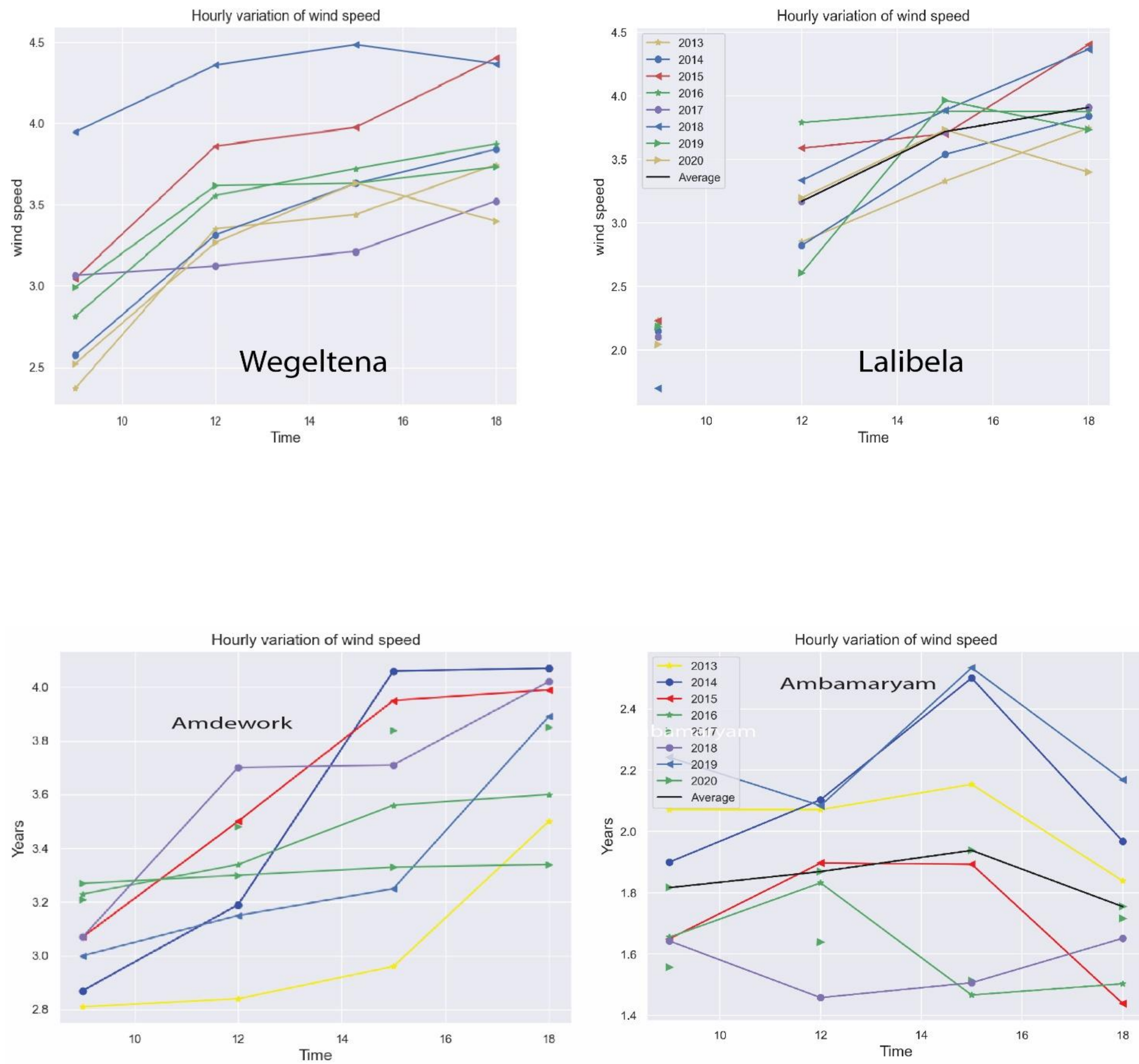


Figure 4: Hourly variations of wind speeds of four sites

4.1.2 Monthly average wind speeds and standard deviations for the entire years

Figure 6 shows the average monthly variance in wind speed at four different locations. Site Lalibela has the highest average wind speed, reaching a peak in May of 3.15 m/s. Nonetheless, August saw the lowest average wind speed of 1.82 m/s at Site Wegeltena, which is where the lowest wind speed is recorded. Using eight years of meteorological data from 2013 to 2020, the windiest months in the research region of the four sites are determined at Wegeltena using monthly average wind speed data, as seen in the aforementioned figure 6.

Since all of the stations experience their windiest months in March, April, and May—the "Belg" seasons—when the amount of water available for hydropower is diminishing and occasionally insufficient to generate hydropower during the dry season—wind energy and hydroelectric energy complement each other well. With average wind speeds of 2.77, 3.15, and 2.76 m/s, respectively, May is the windiest month in Wegeltena, Lalibela, and Ambamaryam, with the exception of Amdework, as shown by the results in figure 6. At an average wind speed value of 3.03 meters per second, April proved to be the windiest month at Amdework Station. August was the month with the lowest wind speed recorded across all stations.

Seasonal fluctuations in the climate of the Wello Highlands plateau zone are consistent with the highest average monthly wind speeds found in the months of January to June and October to November at most of the Sites. Previous research in various areas also looked into these variances (Eshete et al., 2021). Nevertheless, July to September known as the "Kiremt" season had the lowest wind speeds.

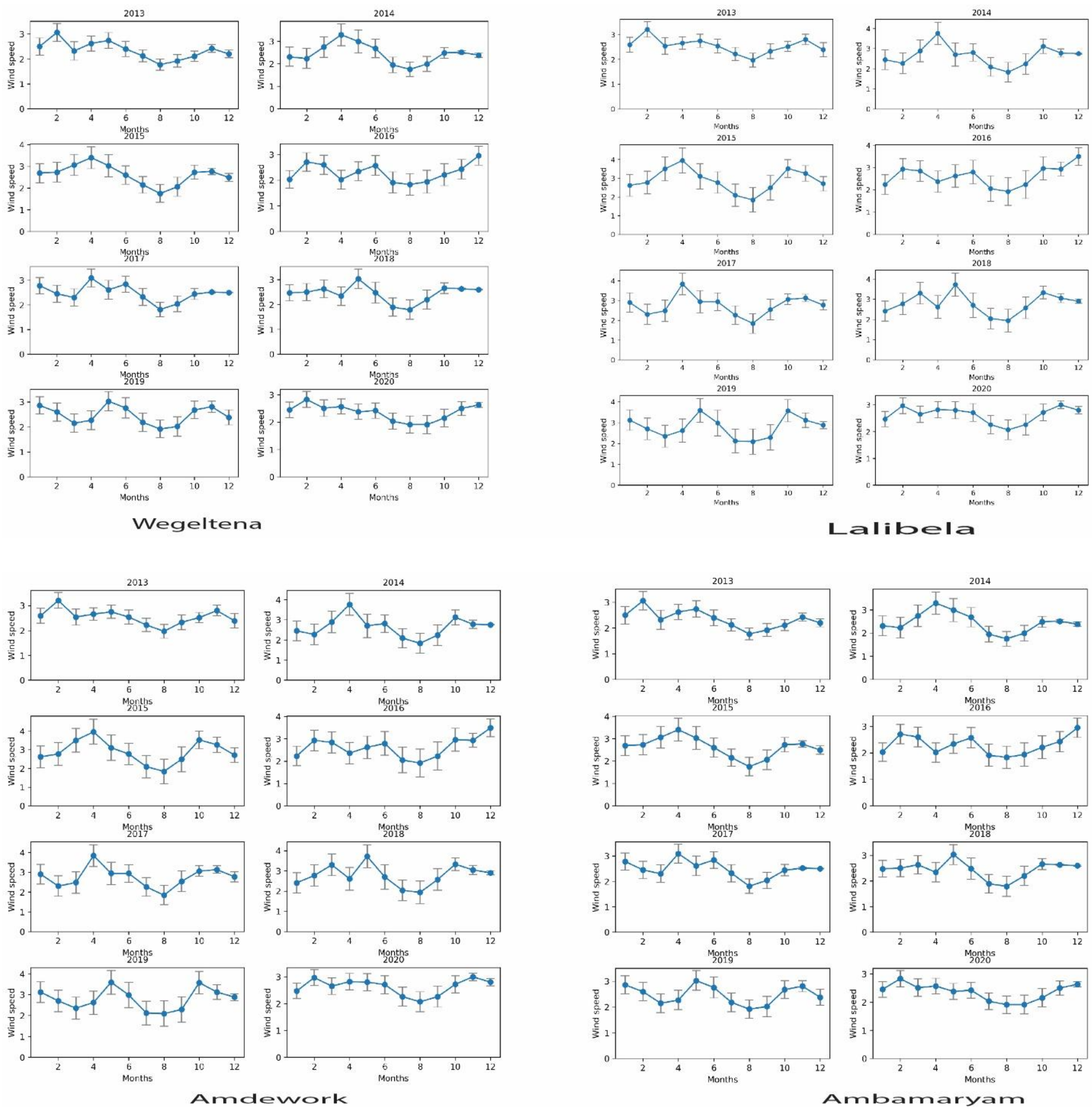


Figure 5:- monthly average wind speeds and standard deviations

4.1.3 Extrapolated wind speed

With a hub height of 10 meters as its starting point, Figure 7 illustrates the discussion of projected wind speed at 50 and 100 m heights. Wind speeds are higher between 50 and 100 meters than they are at 10 meters due to the effect of wind shear, which causes the wind to pick up speed as it rises above the ground. Wind shear, which is caused by friction between the wind and the earth, slows down the wind near the surface. Typically, wind turbines are erected between 60 and 100 meters above the ground, where wind patterns are more stable and the speeds are higher. (Ramon et al., 2020).

This is because the wind accelerates and encounters less friction as it moves higher, leading to higher wind speeds at greater heights. Accurately assessing the potential and performance of wind turbines at greater heights is of utmost importance for optimizing wind energy generation efficiency and output. As we have understood in Figure 7, the highest wind speed was recorded at 100 m height at Lalibela in May with a value of 6.3 m/s.

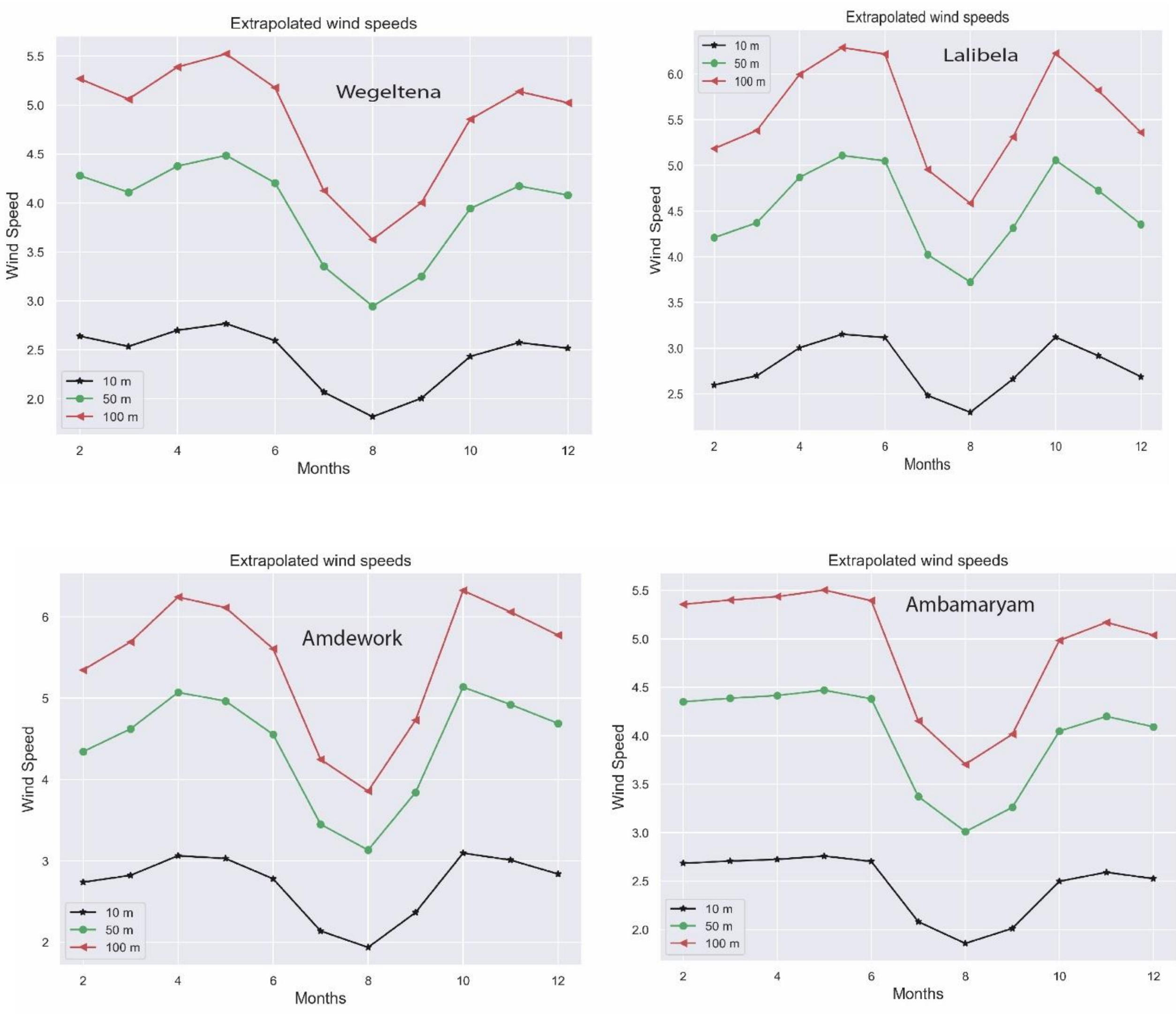


Figure 6 Extrapolated wind speeds of wegeltena (a), Lalibela (b), Amdework (c) and Ambamaryam (d)

4.1.4 Extrapolated wind power density

Figure 8 displays the mean wind power density over a period of time in four different Ethiopian locations of Wello highlands: Lalibela, Amdework, Ambamaryam, and Wegeltena. From each graph's, y-axis displays the wind power density in watts per square meter (W/m2), while the x-axis displays the current month. Each graph of three lines represents the wind power density at three distinct elevations of 10, 50, and 100 m.

In Lalibela, the wind power density peaks in May with an average wind power density value of 155 W/m^2, whereas Wegeltena has the lowest wind power density on August with an average value of 30 W/m^2. In Lalibela, Wegeltena, and Ambamaryam have the highest wind power density on May, while August on all Sites have the lowest wind power density. On the other hand, at Amdework, the months of April has the highest wind power density, while August has the lowest. Overall, the figure shows that Ethiopia has a good potential for wind power generation. The wind power density is highest at high altitudes, and it is generally highest during the dry season. However, the wind power density varies throughout the year, so it is important to consider this when planning wind power projects.

The phenomenon of wind shear, which causes the wind to speed up as it gets farther from the ground, accounts for the reason why wind power density is higher at 50 and 100 m heights than at 10 m heights. The ground-wind friction causes the wind to slow down close to the surface, resulting in wind shear. Wind turbines are typically installed at hub heights between 60 and 100 m because of this phenomenon: as the wind increases in altitude, it encounters less friction and accelerates, leading to higher wind speeds and potentially higher wind power densities at greater heights. This study also investigated previously with similar results of this study (Ramon et al., 2020).

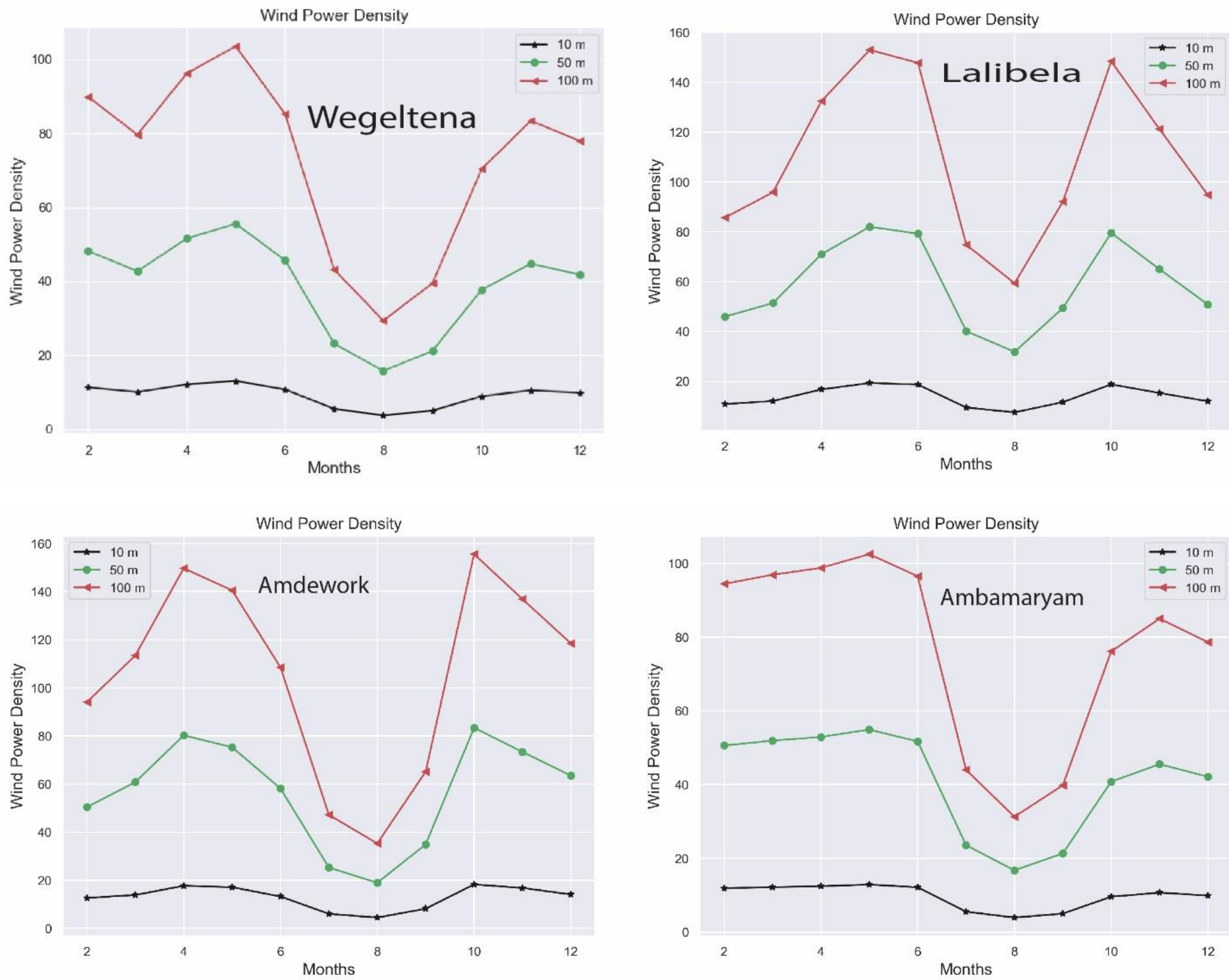


Figure 7: Extrapolated wind power density

4.2 Wind Speed Weibull distribution analysis

Two different functions, the probability density function and the cumulative distribution function, provide a detailed description of the fluctuations in wind velocity. Thorough the representation of the probability distribution of wind velocities at various levels is given by the probability density function, which also sheds light on the possibility of running into particular wind speeds within a given range. Conversely, the cumulative distribution function provides a cumulative viewpoint by showing the likelihood that the wind speed will not surpass a specific value. Together, these functions offer a comprehensive understanding of wind behavior, facilitating informed decision-making in various fields such as renewable energy planning, environmental monitoring, and risk assessment

4.2.1 Wind speed Weibull probability density function

Figure 9 illustrates the sample of code that is provided fits a Weibull distribution to a set of wind speed data and plots the distribution's probability density function (PDF). The Weibull distribution is a popular choice for modeling wind speed data because of its ability to accurately capture the distribution's shape, which can change based on the location and time of the data. The interpretation of the Weibull distribution fitting result is as follows: The distribution's shape is represented by the shape parameter, or shape.

Perfect Weibull distributions have a shape parameter of 1, but distributions can deviate from perfect Weibull shapes when the shape parameter is less than or greater than 1. The distribution's tail heaviness can be determined using the shape parameter. The location parameter (loc) indicates the distribution's location on the x-axis, depending on whether the distribution has a longer tail on the left or right. The distribution can be shifted along the x-axis to align it with the data's mean by using this technique. The scale parameter, or scale, shows how widely the distribution is distributed. The plot of the distribution shows how the width of the distribution can be changed to make it narrower or wider.

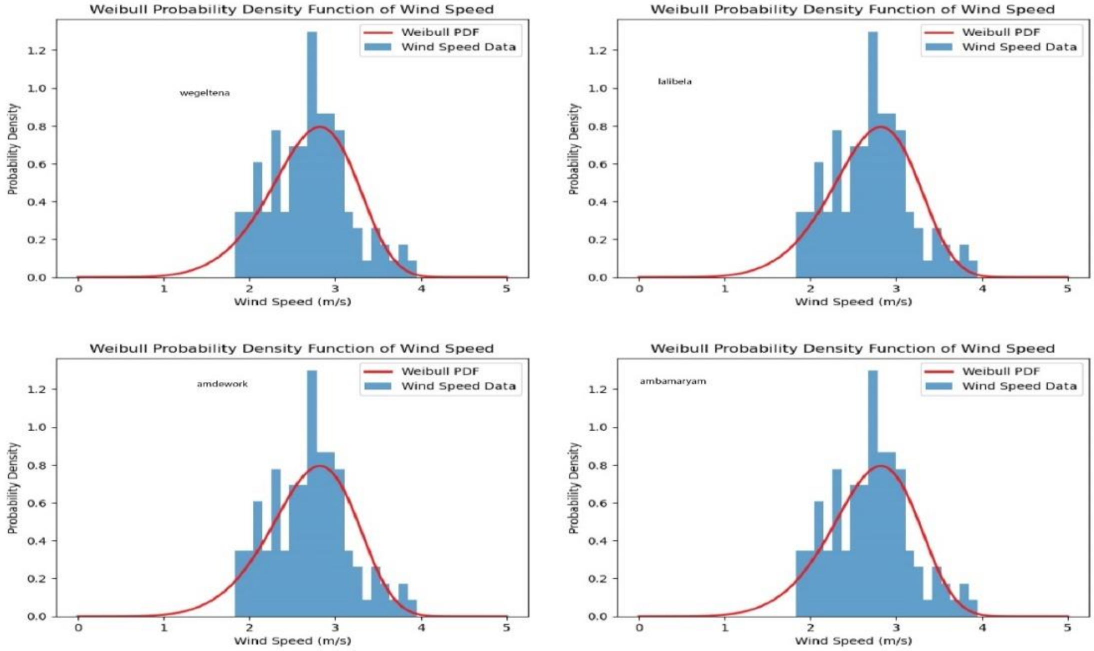


Figure 8: Wind speed Weibull probability density function on wind speed of Wegeltena (a), Lalibela (b), Amdework (c) and Ambamaryam (d)

4.2.2 Wind speed cumulative distribution function

Figure 10 describes by utilizing the Weibull distribution, the code extract provided computes the cumulative distribution function (PDF) for wind speeds. If the wind speed is less than or equal to a given value, the probability is represented by the CDF. One popular probability distribution for simulating wind speeds is the Weibull distribution; the CDF can reveal information about the probability that a given wind speed will occur.

The illustration of the Weibull CDF plotting probability of wind speeds being less than or equal to a given value is the code's output. A wind speed's value is represented by the x-axis, and its probability, expressed as a probability, is represented by the y-axis. Visualizing the dataset's wind speed distribution and the degree to which the Weibull distribution fits the data are both made possible by the plot. To accurately forecast wind energy and place wind turbines in the best possible locations, it is essential to understand the CDF of wind speeds. Insights into the probability of varying wind speeds can be gained by computing the CDF of wind speeds using the Weibull distribution. This information can assist in informing decisions regarding the generation of wind energy.

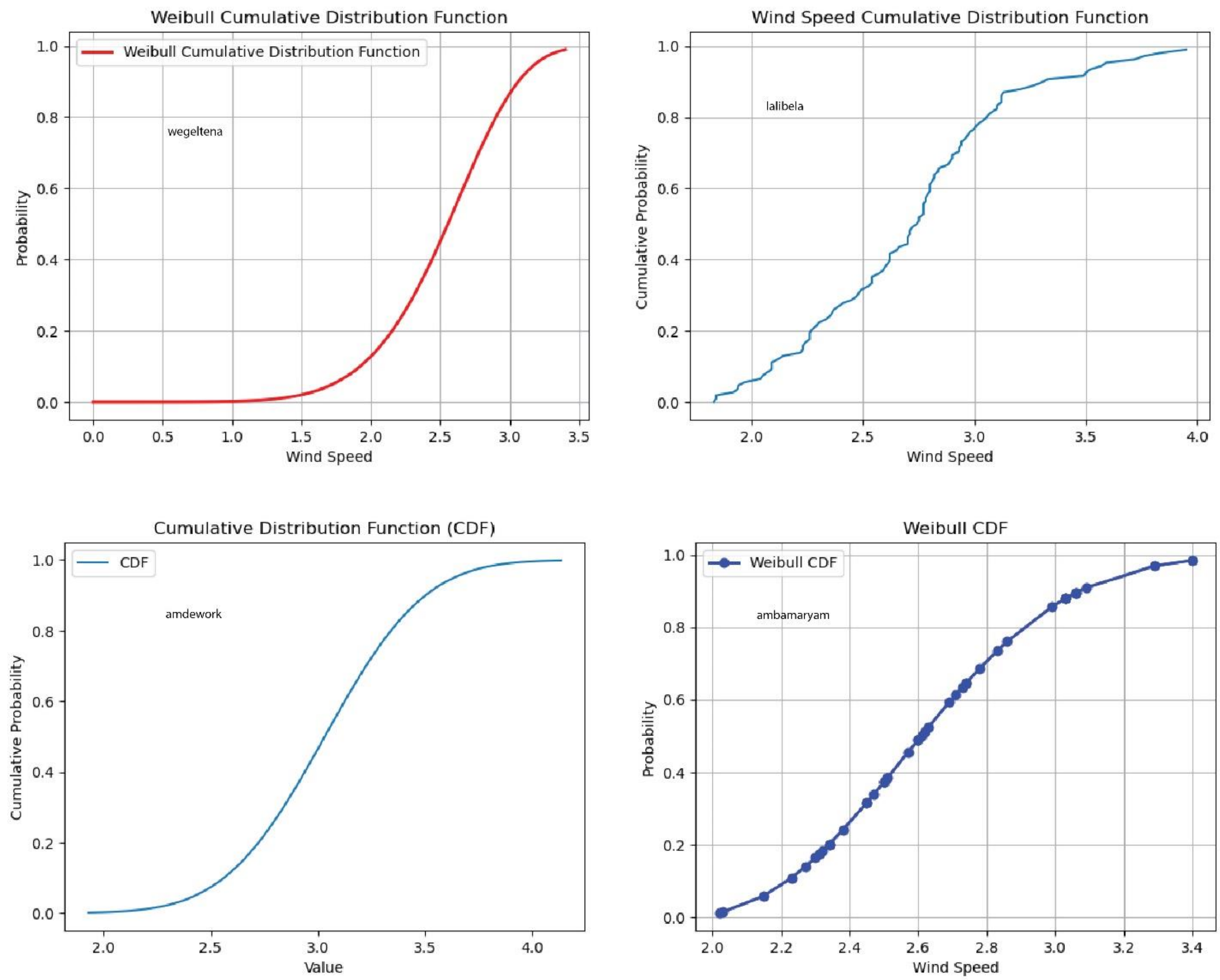


Figure 9 Wind speed Weibull cumulative distribution function

4.3. Wind Power Calculation

Determining the theoretical and actual generation capacity of wind farms is a critical step in the development and optimization of renewable energy systems. The wind data extrapolation method and the model wind turbine method are the two main approaches for computing wind power.

The model wind turbine approach estimates the power output based on wind speed data by using mathematical models of wind turbines. Planning and optimizing wind power projects require the ability to calculate wind farm power generation on a large scale, which is made possible by this method. The following are the power calculation estimations of four Sites based on the power law and the extrapolated wind speed at 50 m.

For any wind stream with speed v (m/s), cross-sectional area A (m^2), and

air density *(ρ*=1.225$e^{Hp/^{-z}}$ kg/m3), the theoretical power (*P*) that is available can be obtained from (Hadi, 2015)

The total wind power density, P/A, is the total available power per unit area

4.3.1 Wegeltena wind power estimation

Let say, the diameter of the turbine be 50 m, then the wind power of Wegeltena is: -

$A = \pi r^2$

$A = \pi * (D/2)^2$

$=3.14*(50/2)^2$

$=1962.5\ m^2$

V=3.94 m/s

$1.23=\rho=1.225e^{3100/8400}$

P=0.5*1.23*1962.5*$(3.94)^3$=73819.9 W=**73.819** KW

To calculate the wind power potential for a community, you would need to gather information about the average wind speeds in the area, air density, height, and the estimated energy needs of the community. Here is an estimation example of how to calculate wind power for a community using a consideration case study:

Case study: Let's say a rural community in the Wegeltena area is interested in installing a wind turbine to provide electricity to its residents. Let's say the community has an average annual energy consumption of 500,000 kWh and is located in an area with an average wind speed of 3.94 meters per second at a height of 50 meters.

Step 1: To estimate the energy production of a wind turbine, we would need to know the power rating of the turbine and the capacity factor. The power rating is the maximum power output of the turbine, while the capacity factor is the percentage of time that the turbine is generating power at its maximum capacity.

For this case study, let's assume that a 1.5 MW wind turbine with a capacity factor of 30% is used. This means that the turbine would generate an average of 1.5 MW x 0.30 = 0.45 MW of power.

Step 2: Determine how many turbines are required. The community's annual energy consumption must be divided by the energy output of a single turbine in order to determine the number of turbines required to meet the community's energy needs. 500,000 kWh divided by 0.45 MW times 8760 hours annually equals 126.8 = 127 turbines.

This calculation assumes that the turbines would operate at their maximum capacity for the entire year, which is not realistic. In reality, the turbines would generate more power during periods of high wind speeds and less power during periods of low wind speeds. So according to the estimation of the study, the site of Wegeltena has the potential to generate 500,000 kWh within 127 turbines, which meets the electrification demand of the community of the site.

4.3.2 Lalibela Wind Power Estimation

Assume that the turbine's diameter is 50 m, its area is 1962.5 m^2, and the Lalibela wind power is utilized to calculate the potential wind energy generation for both the community and the grid. This estimate was calculated using the data available to the community; thus, it does not reflect the actual installation.

$A = \pi * (D/2)^2$

$=3.14*(50/2)^2$

$=1962.5\ m^2$

$V=4.5$ m/s

$P=0.5*1.23*1962.5*(4.5)^3=109982$ W=**109.982** kW

4.3.2 Amdework Wind Power Estimation

Let the diameter of the turbine be 50 m.

$A = \pi * (D/2)^2$

$=3.14*(50/2)^2$

$=1962.5\ m^2$

$V=4.13\ m^2$

$P=0.5*1.23*1962.5*(4.13)^3=85022.7\ W=85.0227\ KW$

4.3.2 Ambamaryam Wind Power Estimation

Let the diameter of the turbine be 50 m.

$$A = \pi * (D/2)^2$$

$$=3.14*(50/2)^2$$

$$=1962.5\ m^2$$

$$V=4.008\ m^2$$

$$P=0.5*1.23*1962.5*(4.008)^3=77.7084\ W$$

4.4 Artificial Intelligence Models

This section presents the key findings from modeling wind speed and wind power density predictions using four different machine and deep learning algorithms: XGBoost, Gradient Boosting, artificial neural networks (ANN), and long short-term memory (LSTM). The models were trained on a weather dataset consisting of features like precipitation, humidity, temperature, sunshine hours, wind directions, pressure, and the target variable wind speed and wind power density. The Python code reads a CSV file and drops the rows with missing values. This is important because missing values can affect the quality of the data and the performance of the AI models. The code then scales the data using MinMaxScaler.

This is important because it ensures that all features are on the same scale and prevents some features from dominating others.

The code also checks for outliers using box plots. This is important because outliers can affect the performance of the machine learning models and need to be handled appropriately. The time-series plots of the raw data indicated the presence of seasonality. After handling missing values and outliers, the data was scaled to make it stationary. The scaled data did not show any increasing or decreasing trends or heteroscedasticity, thereby confirming stationarity. This allowed the target to be included in the feature set. The dataset was divided into a training set (80%) and a testing set (20%) for modeling. Using the RMSE loss function, the training objective was to minimize the variance between the predicted and actual values. The adaptive momentum estimation (ADAM) optimizer, which combines the benefits of AdaGrad and RMSProp, was utilized for optimization.

4.4.1 Wind Speed Models Assessment

4.4.1.1 Extreme Gradient Boosting

As we have understood from below Table 5 and Figure 11, the Extreme Gradient Boosting model's performance for predicting wind speed results is generally not best based on evaluation metrics. **The Extreme Gradient Boosting model** had an R^2 score of 0.52, 0.39, 0.50, and 0.37 at Wegeltena, Lalibela, Amdework, and, Amba Maryam respectively, which indicates that the XGBoost model explains 52%, 39%, 50%, and 37% of the variance in the actual wind speed values respectively. The performance of this algorithm is good at Wegeltena and Amdework, but it performs poorly at Lalibela and Ambamaryam.

MSE (Mean Squared Error): MSE values at all sites are below 0.08, which indicates accurate predictions, with the slight performance squared errors between predicted and actual wind speeds on average being small. MAE is also below 0.02, and lower values are preferred on MSE and MAE. Overall, the XGBoost model does not have the best predictive capability for the wind speed time series based on the available data. From the four sites, at Wegeltena, the model performs better than at the rest areas. The study was previously investigated at the area of Somalia region in Ethiopia with the coefficient determination (R^2) value of 88%, (Awale, 2021). This implies extreme gradient boosting algorithms are favorite for wind energy predictions.

Table 5:- Extreme Gradient Boosting Evaluation Metrics

Model	R^2 Score	MAE	MSE
Wegeltena	0.52	0.01	0.08
Lalibela	0.39	0.10	0.02
Amdework	0.50	0.08	0.0097
Ambamaryam	0.37	0.08	0.01

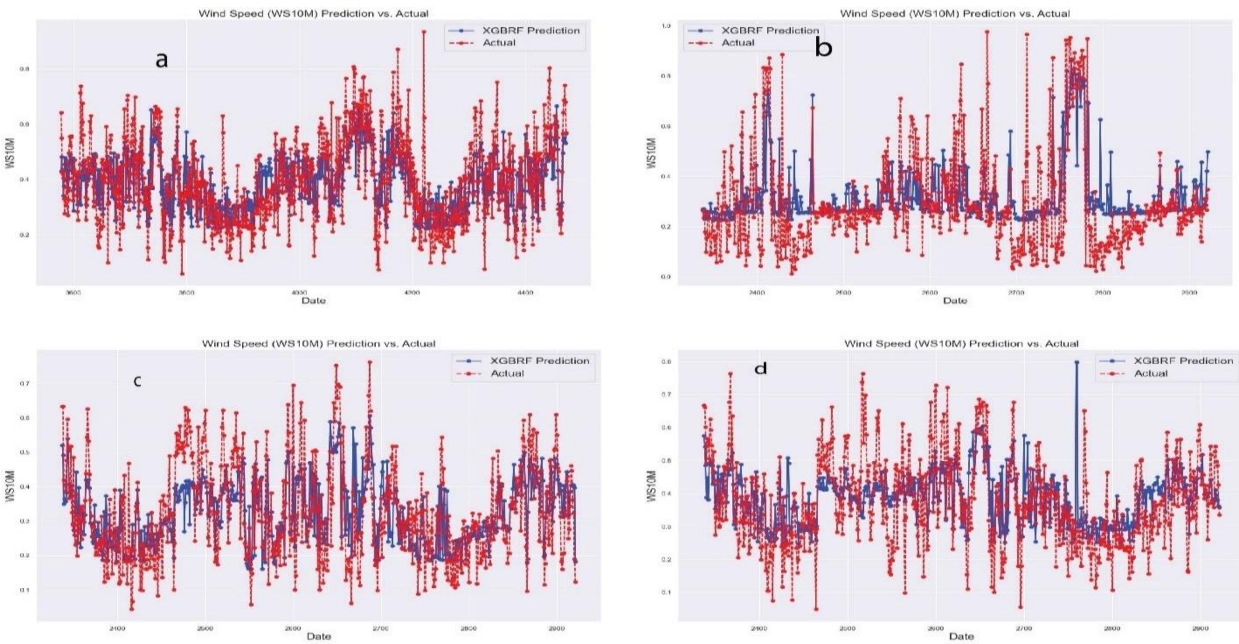


Figure 10: Extreme Gradient Boosting plot on wind speed of wegeltena (a), Lalibela (b), amdework (c) and ambamaryam (d)

4.4.1.2 Gradient Boosting

Figure 12 and Table 6 illustrates, the gradient boosting model's performance for predicting wind speed results, that is good at four sites based on evaluation metrics. **The Gradient Boosting model** had an R2 score of 0.56, 0.40, 0.52, and 0.48 at Wegeltena, Lalibela, Amdework, and Ambamaryam respectively, which indicates that the Gradient Boosting model explains 56%, 40%, 52%, and 48% of the variance in the actual wind speed values respectively at four sites.

The performance of this algorithm is good at Wegeltena and Amdework, but it performs poorly at Lalibela and Ambamaryam. MSE (Mean Squared Error): MSE values at all sites are below 0.03, which indicates more accurate predictions, with the slight performance squared errors between predicted and actual wind speeds on average being small. MAE is also below 0.1; lower values are preferred for both MSE and MAE. Overall, the gradient boosting model indicates the least predictive capability for the wind speed time series based on the available data. From the four sites, at Wegeltena, the model performs better than the other sites.

Table 6: Gradient Boost Metrics on Wind speed

Model	R^2 Score	MAE	MSE
Wegeltena	0.56	0.075	0.0097
Lalibela	0.40	0.105	0.022
Amdework	0.52	0.075	0.009
Ambamaryam	0.48	0.08	0.01

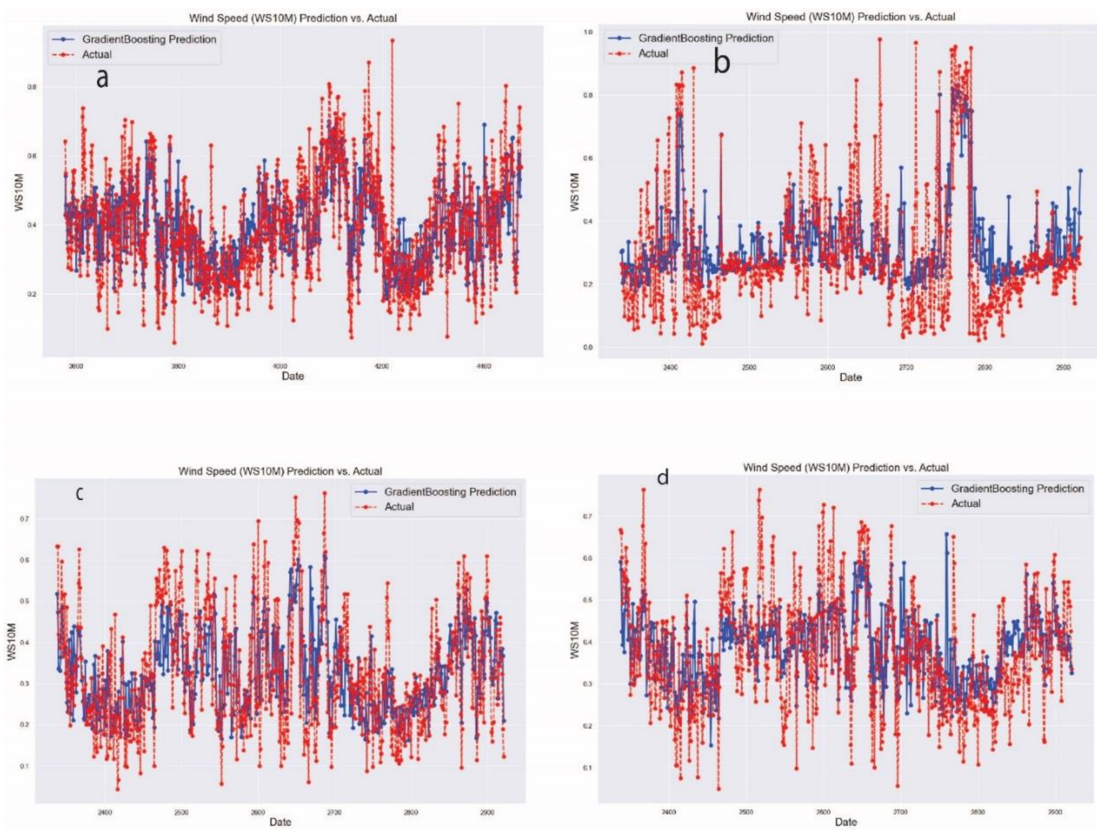


Figure 11: Gradient Boost plot on wind speed of wegeltena (a), Lalibela (b), amdework (c) and ambamaryam (d)

4.4.1.3 Artificial Neural Network

Based on below Fig. 13 and Table 7, the ANN model performance for predicting wind speed Results were okay, but not the best at four sites based on evaluation metrics. It needs optimization of the models. R^2 (Coefficient of Determination): The R^2 score of 0.575, 0.63, 0.59, and 0.61 at Wegeltena, Lalibela, Amdework, and Ambamaryam respectively, indicates that the ANN model explains 58%, 63%, 59%, and 61% of the variance in the actual wind speed values of each sites respectively. This is very high and shows the prediction has good explanatory power.

The mean squared error MSE values at all sites are below 0.1, which indicates more accurate predictions, with the moderate squared errors between predicted and actual wind speeds on average being small. MAE is also below 0.1; lower values are preferred for both MSE and MAE. Overall, the ANN model already shows medium predictive capability for the wind speed time series based on the available data.

*Table 7: **Performance of ANN model on WS***

Model	R^2 Score	MAE	MSE
Wegeltena	0.575	0.0740	0.00947
Lalibela	0.63	0.105	0.022
Amdework	0.59	0.304	0.152
Ambamaryam	0.61	0.08	0.01

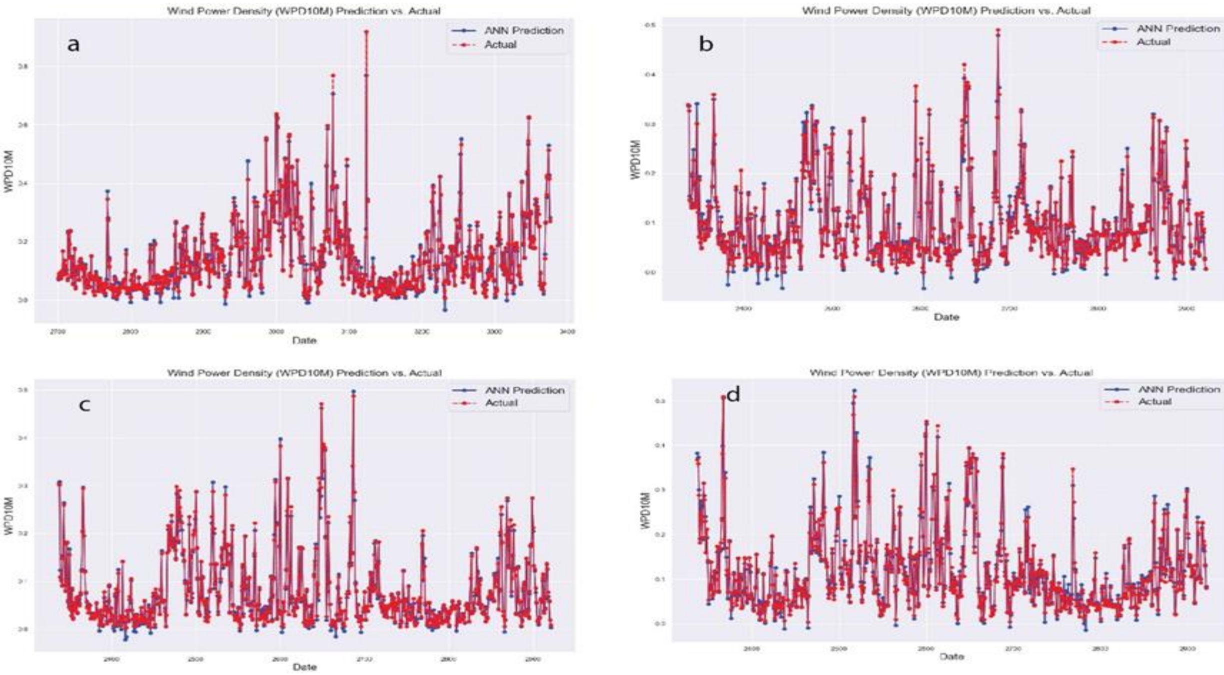


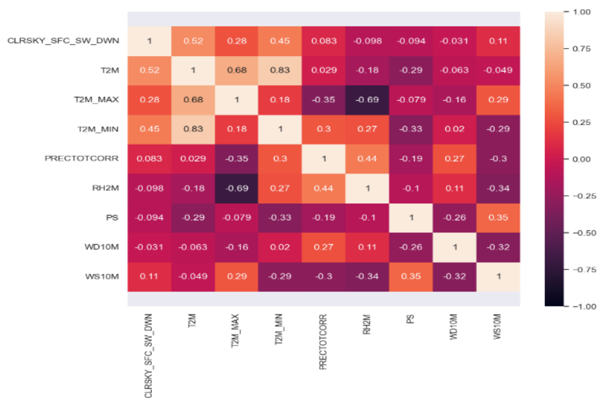
Figure 12 The plot of wind power density on ANN

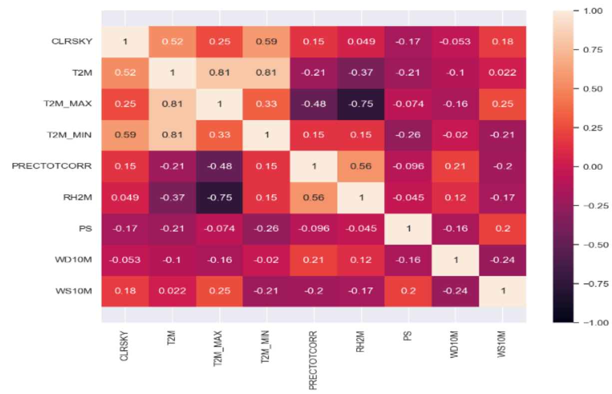
Correlation of the Parameters

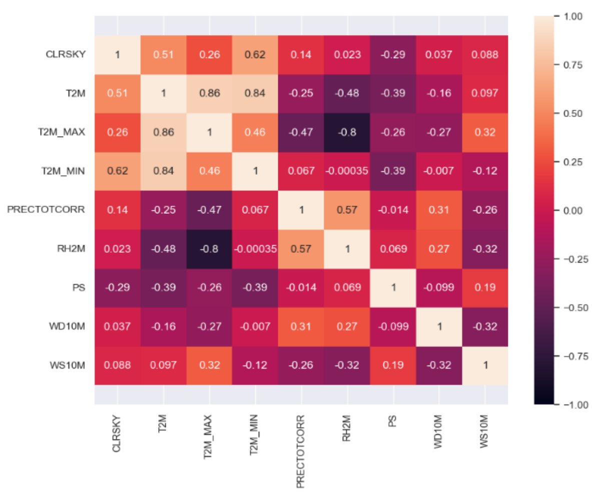
Below Figure illustrates about the correlation of the parameters. The most grounded positive relationship (0.81) is between T2M (total temperature) and T2M_MAX (the most extreme temperature). This exceptionally solid relationship makes instinctive sense since the greatest temperature for a given day is closely related to the total temperature. There is also a solid positive relationship (0.59) between sunshine (a clear sky) and T2M_MIN (the least temperature). More clear skies appear to be related to higher temperatures. Precipitation contains a tolerably solid negative relationship with T2M_MAX (-0.48). More precipitation tends to be related to lower, more extreme temperatures.

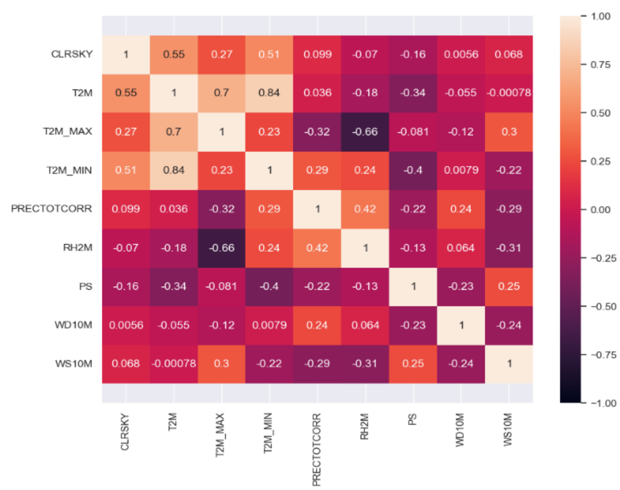
Relative humidity is decently negatively related to both T2M (-0.37) and T2M_MAX (-0.75). Higher temperatures are associated with lower stickiness. Most meteorological parameters have good relationship with wind speed or wind direction. The exemptions are the little relationships between precipitation and wind heading (0.21), wind speed, and the most extreme temperature

(0.25). So, in the rundown, the most grounded relationships appear to be related to distinctive temperature factors, as anticipated. Precipitation and stickiness also relate negatively to temperatures. Most relationships align well with climate instinct/character.









4.4.1.4 Long Short-term memory (LSTM)

Wind Speed Parameters Plot of LSTM Training-Test and Loss

The test dataset was used to assess the models following training. Additionally, the research provided graphical depictions of test loss and training loss over epochs for the LSTM in wind speed forecasting, as shown in Fig. 13. Through the display of loss values over epochs, these statistics provide valuable insights into the models' performance and their convergence/improvement across training. To put it another way, they offer data regarding how precise and reliable the models evolve over time as they learn from the data and make gradual parameter adjustments.

The accuracy and dependability of the predictive models employed in wind-related forecasting must be evaluated using this data. The study emphasizes the significance of assessing these models' effectiveness across a range of temporal granularities and the capturing of the time series data perfectly, that indicates the LSTM model is perform the wind prediction exactly with four study areas.

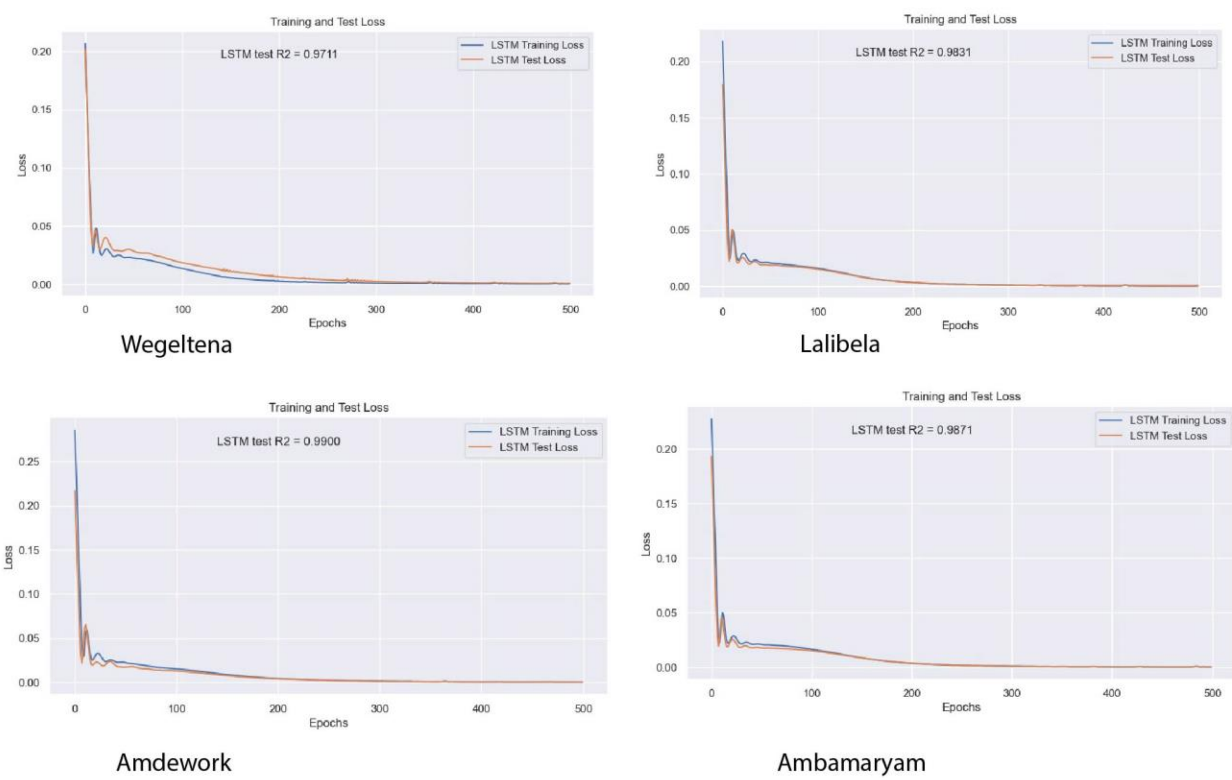


Figure 13 Training and test loss of the wind speed prediction models at four sites

Training and Test Loss Plot LSTM Model on Wind Speed

From the Fig 14 and Table 8, the LSTM model performance for predicting wind speed results are the best at four sites basd on evaluation metrics. R^2 (Coefficient of Determination): The R^2 score of 0.97, 0.983, 0.99, 0.987 at Wegeltena, Lalibela, Amdework and Ambamaryam respectively indicates that the LSTM model explains 97% ,98.3%, 99% and 98.7% of the variance in the actual wind speed values respectively. This is very high and shows the predictton have perfect explanatory of wind power.

MSE (Mean Squared Error): MSE values at all sites are below 0.001 that indicates more accurate predictions, with the best squared errors between predicted and actual wind speeds on average being small. MAE also below 0.001, lower values are preffered for both MSE and MAE.

Overall the LSTM model already shows the best predictive capability for the wind speed time series based on the available data. From the four sites, at Amdework, the model performs superior over other sites. This results were described or investigeted by previous studies with the cofficient determination (R$^{2)}$ of LSTM value of 99.3% (Natei et al., 2024), this demonistrate my work approximatly similar performance of the previous study for wind energy prediction with best prediction, so this model is the latest one to predict wind energy availability

Table the results of LSTM on wind speed at Four Study Sties

Table 8: - performance of LSTM on WS

Model	R^2 Score	MAE	MSE
Wegeltena	0.97	0.002	0.0008
Lalibela	0.983	0.001	0.0002
Amdework	0.99	0.0015	0.0003
Ambamaryam	0.987	0.001	0.0002

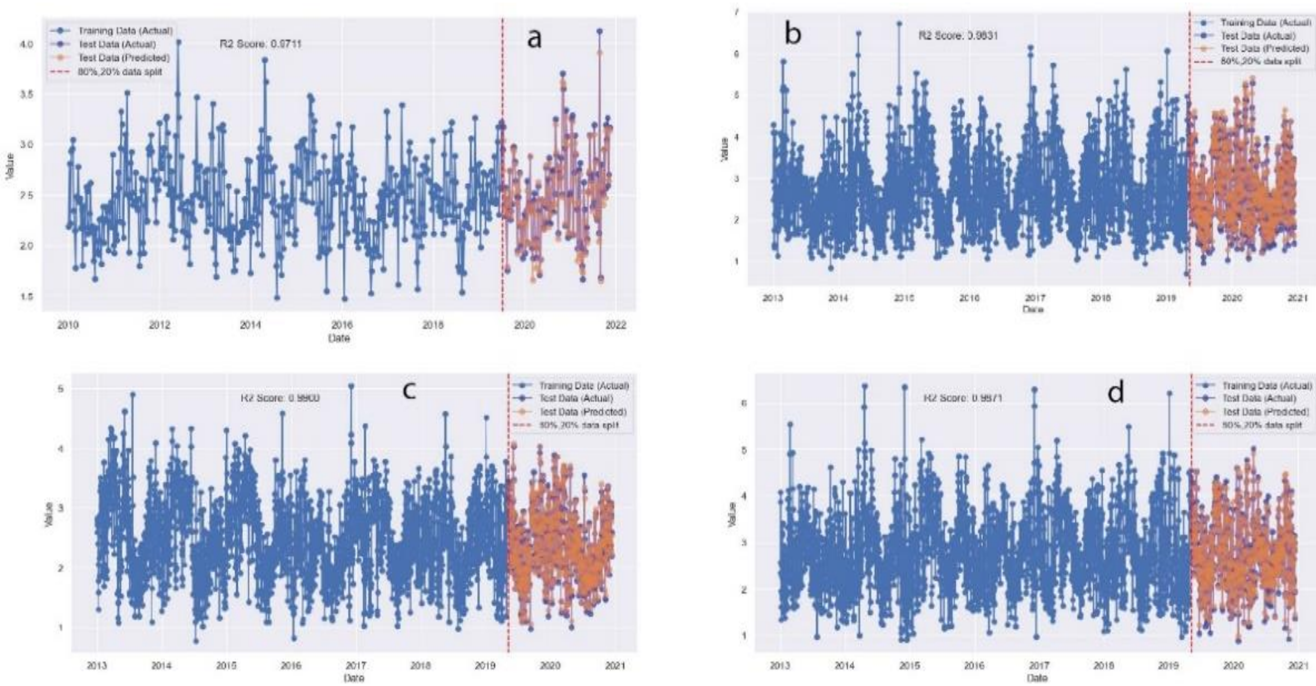


Figure 14: - LSTM plot on wind speed of Wegeltena (a), Lalibela (b), Amdework (c) and Ambamaryam (d)

4.4.2 Wind Power Density Models Assessment

We have seen above about the model results and performance of wind speeds with different models and their metrics, while this section showed that the wind power density algorithms for four sites with their performances.

4.4.2.1 Artificial Neural Network

As Figure 15 and Table 9 illustrates, the ANN model in wind power density prediction achieved the best performance at all sites, with an MSE of 0.000009 and a MAE of 0.007 for four stations, which indicates the model performed accurately at all sites. The high R^2 of 0.989, 0.987, 0.994, and 0.988 at Wegeltena, Lalibela, Amdework, and Ambamaryam, respectively, also indicates ANN explains the highest variance in the time series. The ANN model provides the most accurate one-step-ahead predictions in this work. All sites perform accurately with the algorithm ANN, but the ANN performs the best at Amdework (99.4%).

Table 9: MSE, MAE, and R^2 scores for the ANN model on WPD

Model	R^2 Score	MAE	MSE
Wegeltena	0.989	0.007	0.00016
Lalibela	0.987	0.006	0.000008
Amdework	0.994	0.004	0.000004
Ambamaryam	0.988	0.007	0.000009

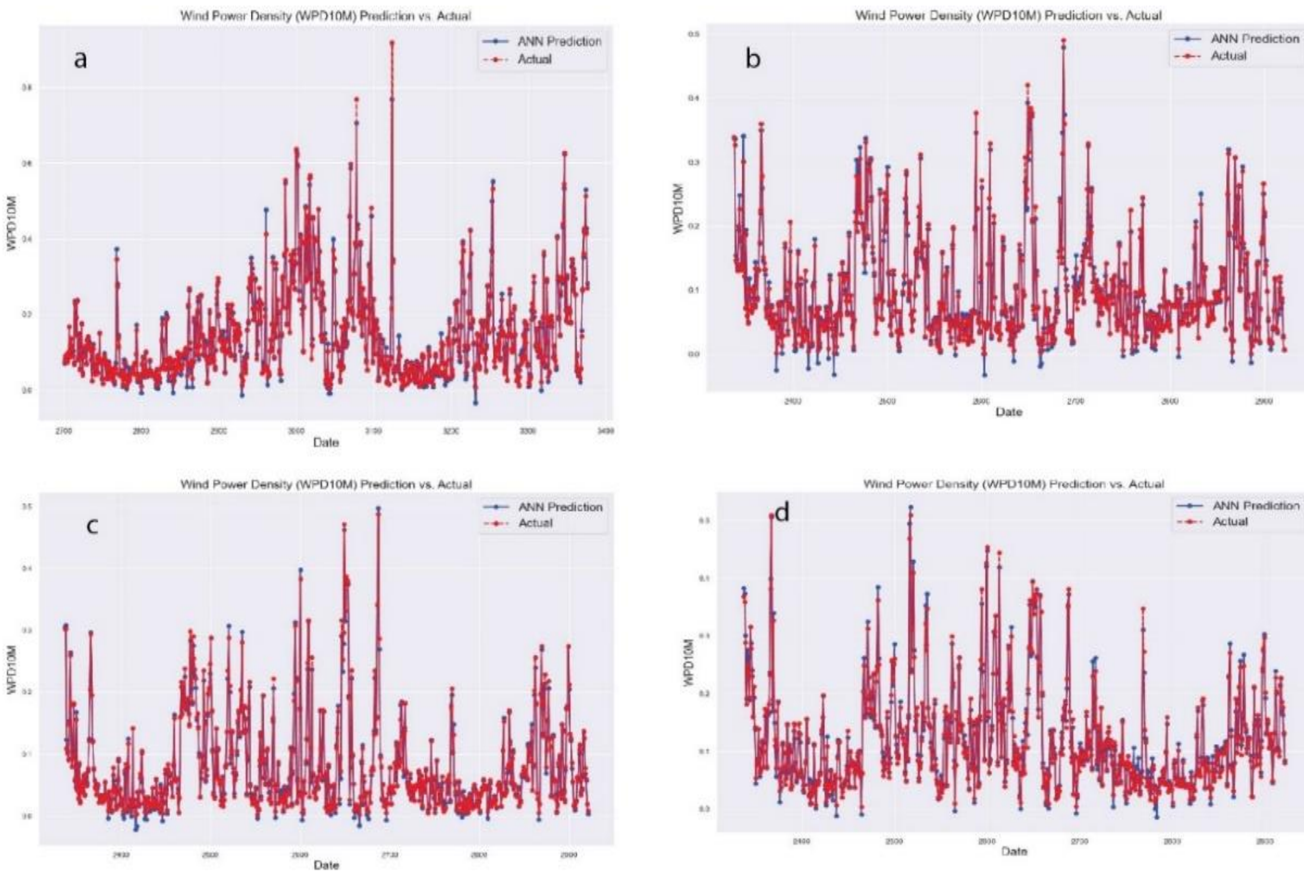


Figure 15: - ANN plot on Wind power density of Wegeltena (a), Lalibela (b), Amdework (c) and Ambamaryam (d)

4.4.2.2 Long Short-term memory (LSTM)

Figure 16 and Table 10 illustrates the performance of the LSTM model for predicting time series data of wind power density. The mean squared error, mean absolute error, and R-squared scores indicate how well the model fits the data and makes predictions perfectly. A lower MSE and MAE and a higher R^2 score are desirable, indicating better model performance at all sites; the best model performs at Wegeltena. As a general rule, the LSTM model for wind power density performs best at all stations in Wegeltena, Lalibela, Amdework, and Ambamaryama, where it scores 99.7%, 98.8%, 99.5%, and 99.4%, respectively, with very low MAE and MSE values.

Table 10: model metrics of LSTM on WPD

Metric	(R^2)	MSE	MAE
Wegeltena	0.997	0.000001	0.0002
Lalibela	0.988	0.0001	0.002
Amdework	0.995	0.000001	0.0001
Ambamaryam	0.994	0.0000001	0.000002

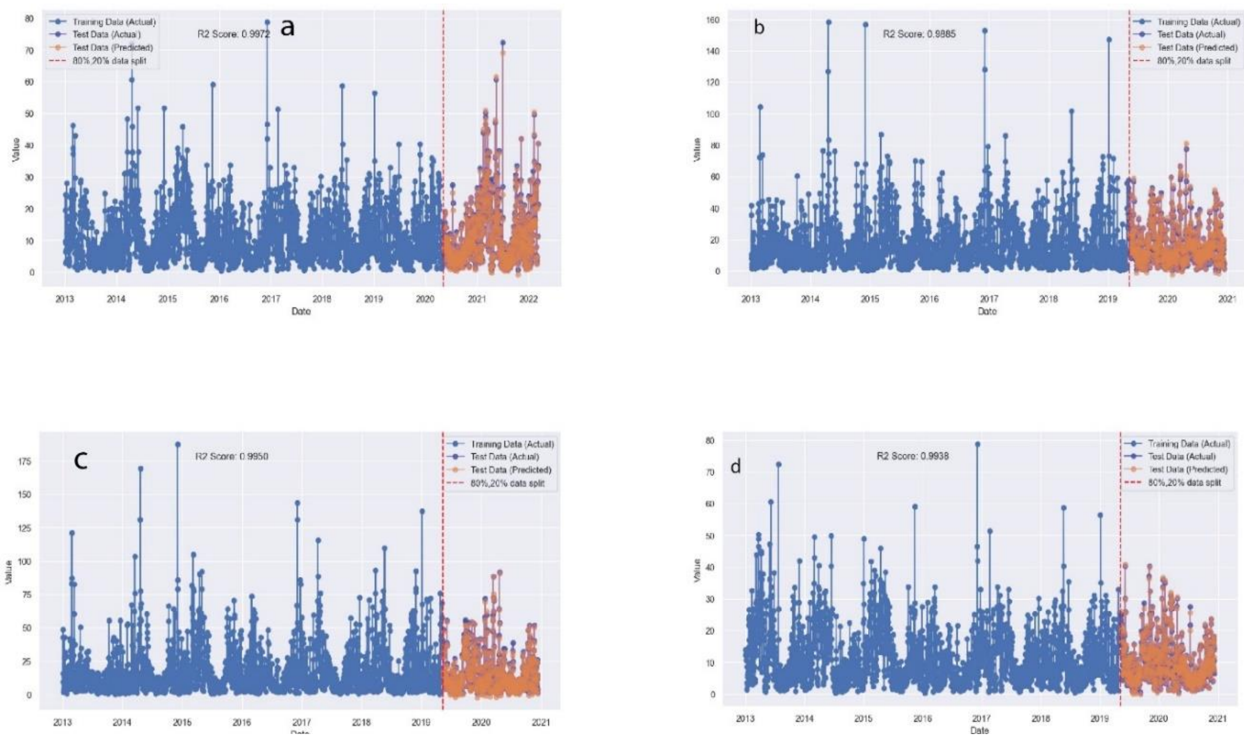


Figure 16:- LSTM plot on wind power density of wegeltena (a), Lalibela (b), amdework (c) and ambamaryam (d)

4.4.2.3 Gradient Boosting

Figure 17 and Table 11 show the metrics evaluations of the algorithms at the four sites. We have understood that the gradient boosting model performance for predicting wind power density results is generally the best based on all evaluation metrics that apply at the four sites. The Gradient Boosting Model R2 score of 0.9977, 0.999995, 0.999994, and 0.99997 at Wegeltena, Lalibela, Amdework, and Ambamaryam respectively indicates that the Gradient Boosting model demonstrates 99.977%, 99.9995%, 99.9994%, and 99.9997% of the variance in the actual wind speed values of each site respectively.

The performance of this algorithm is excellent at all stations; Ambamaryam scored relatively high. Mean Squared Error, MSE values at all sites are below 0.000001, which indicates accurate predictions, with the highest performance of squared errors between predicted and actual wind power density on average being very small, which already approaches zero. This showed that the model performs accurately for all sites with algorithms of gradient boosting of wind power density. MAE is also be close to zero, which means the model evaluation is perfect.

Table 11: Gradient Boost model metrics on WPD

Metric	R-squared (R^2)	MSE	MAE
Wegeltena	0.99977	0.0000004	0.0002
Lalibela	0.999995	0.00000004	0.00002
Amdework	0.999994	0.00000008	0.00002
Ambamaryam	0.999997	0.00000002	0.00001

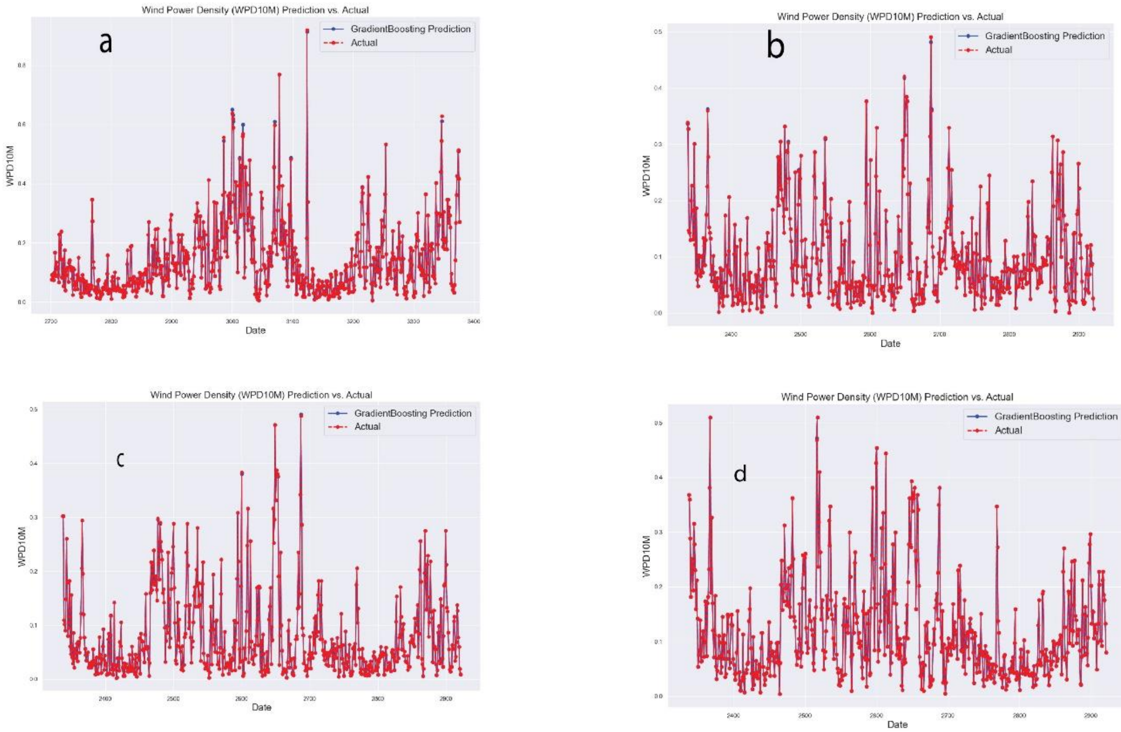


Figure 17: - Gradient Boost on WPD of Wegeltena (a), Lalibela (b), Amdework (c) and Ambamaryam (d)

4.4.2.4 Extreme Gradient Boosting

The metrics evaluations of the algorithms at each of the four sites are displayed in Figure 19 and Table 12. We now know that, across all evaluation measures that are relevant at all four locations, the gradient boosting model performs best in terms of forecasting wind power density outcomes. Wegeltena, Lalibela, Amdework, and Ambamaryam have Gradient Boosting Model R2 scores of 0.9977, 0.999995, 0.999994, and 0.99997, respectively. These scores show that the Gradient Boosting model demonstrates 99.977%, 99.9995%, 99.9994%, and 99.9997% of the variance in the actual wind speed values of each site. This algorithm demonstrates exceptional accuracy across all stations, with Ambamaryam demonstrating the best performance.

The model's accuracy is demonstrated by the maximum performance-squared errors, which are, on average, small differences between the predicted and actual wind speeds. The average squared error (MSE) is less than 0.00004 at every site. Furthermore, the MAE is lower than 0.002. As the errors become closer to zero, lower values of MSE and MAE are preferable since they show that the model is operating accurately. The XGBoost model provides the best overall prediction performance for the wind power density time series based on the available data. Compared to the other four sites, Amdework exhibits superior performance from the model.

Table 12: Extreme Gradient Boost model performance on

Metric	R-squared (R^2)	MSE	MAE
Wegeltena	0.973	0.0004	0.004
Lalibela	0.993	0.00004	0.002
Amdework	0.995	0.00003	0.0017
Ambamaryam	0.996	0.00003	0.0017

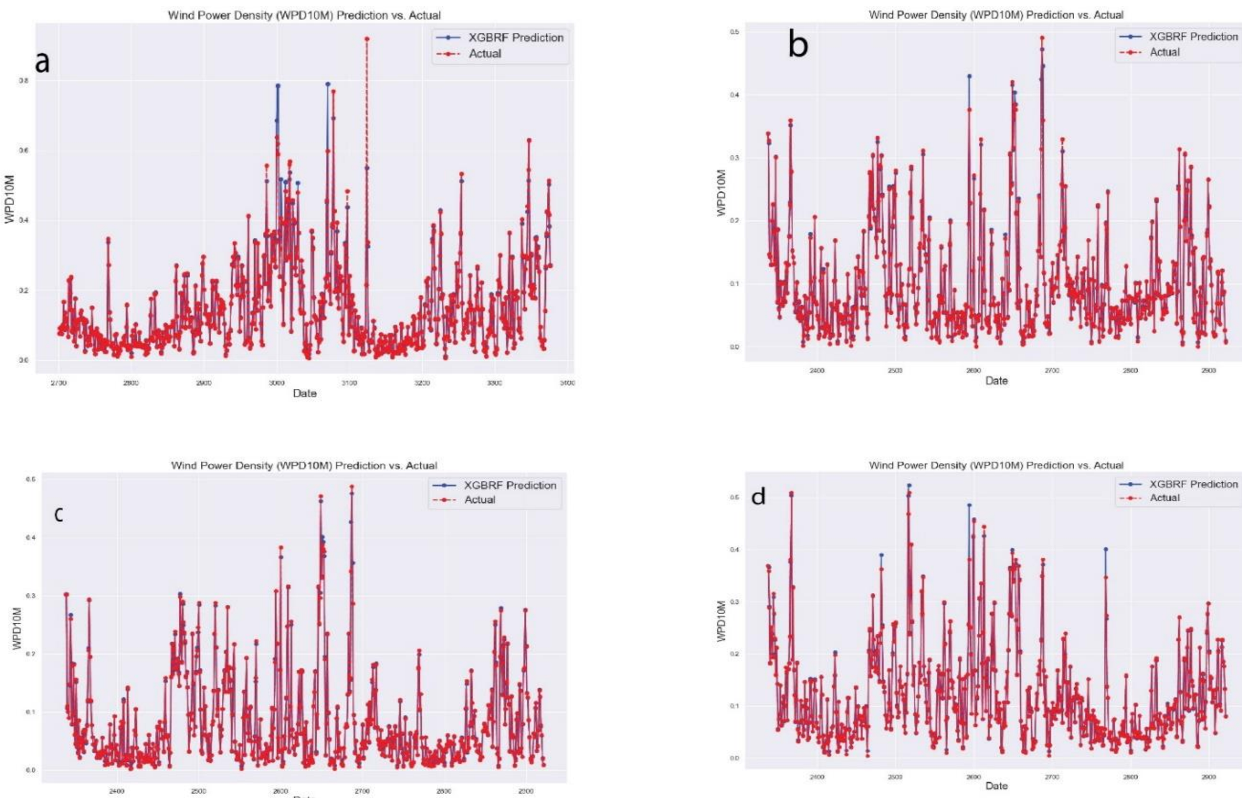


***Figure 18**: XGBoost on WPD of **W**egeltena (a), Lalibela (b), **A**mdework (c) and **A**mbamaryam (d)*

4.5 Models Comparison and Selection

Based on the code and output that were provided, I was referring to the four methods at four stations: XGBoost, Gradient Boosting, ANN (Artificial Neural Network), and LSTM. The results of the four algorithms on wind speed and wind power density at all study sites are summarized in the following: The XGBoost, gradient boosting, and ANN models underperformed in wind speed prediction at all research sites, according to the evaluation metrics. Out of the three models, ANN did better, averaging 58%–63%; this is not the best, but it was still good. XGBoost models, on the other hand, scored the lowest, averaging 37%–52%. This one performs terribly when it comes to predicting wind speed.

LSTM is the recommended model for wind speed forecasts above XGBoost, Gradient Boost, and ANN algorithms, while ANN is not awful for wind speed. The LSTM model performs accurately by scoring above 97%. Regarding wind power density, all four models exhibit excellent performance across all research sites, with scores exceeding 98.8%. However, the gradient boost model outperforms the other models, with a score of almost 99.9%. Overall, the four models—Wegeltena, Lalibela, Amdework, and Ambamaryam—perform extremely well for predicting wind power density at all study sites; that is, there is no discernible difference between the models' outputs.

LSTM models outperform ANN , XGBoost, and Gradient Boost models on the task of wind speed prediction because of:

Temporal Context: LSTMs have recurrent connections that enable them to incorporate contextual information from previous time steps. This allows the model to capture important time-dependent patterns that are useful for forecasting future wind speed or power. Backpropagation through time: The LSTM can backpropagate errors through unlimited time steps, allowing it to learn over many time steps. ANNs can only backpropagate errors through the current input's forward pass.

The LSTM's ability to store, modify, and access longer historical context via its memory cell and gating operations allows it to handle a broader range of sequence modeling problems than a standard ANN. This makes it shine for tasks where long-term dependencies are important. **LSTM models** tend to perform better than ANNs, XGBoost, and gradient-boosted models for predicting wind energy due to the unique challenges of modeling wind patterns over time. Long-term Trends:

There are longer-term seasonal and annual trends in wind patterns that the LSTM can capture via its memory cells. These long-arc patterns are hard to discern with snapshot models like ANNs, XGBoost, or gradient-boosted models alone.

LSTMs are uniquely positioned to model the genuine time-series nature of meteorological systems for wind energy predictions. This makes them exceptionally well-suited for building predictive models of wind patterns and associated energy production compared to models without native sequence understanding. Their architectural features allow LSTMs to strongly outperform on temporally complex sequence forecasting tasks like wind energy prediction.

This research has shown that artificial intelligence (AI) can outperform empirical models for a number of reasons. Firstly, AI allows for the use of different architectures, such as convolutional and recurrent networks, which can outperform empirical models in specific tasks, such as audio synthesis and machine translation. Secondly, AI models, like large language models, can outperform humans on certain tasks, such as question-answering, demonstrating their potential to assist with difficult tasks. Lastly, adaptive methods in deep learning, like Adam, have been observed to outperform stochastic gradient descent across important tasks, indicating that the settings under which they perform poorly in these tasks.

Table 13: Comparison of different artificial intelligence algorithms with performance metrics

Comparison of AI models with different performance metrics												
Station name	**LSTM**			**ANN**			**GBM**			**XGB**		
	R^2	MSE	MAE	R^2	MSE	MAE	R^2	MSE	MAE	R^2	MSE	MAE
Wind speed Performances												
Lalibela	0.983	0.001	0.0002	0.63	0.022	0.105	0.40	0.022	0.105	0.39	0.02	0.10
Amdework	0.99	0.0015	0.0003	0.59	0.15	0.304	0.52	0.009	0.075	0.50	0.0097	0.08
Ambamaryam	0.987	0.0011	0.0002	0.61	0.01	0.08	0.48	0.01	0.08	0.37	0.01	0.08
Wegeltena	0.97	0.002	0.0008	0.58	0.0095	0.07	0.56	0.0097	0.075	0.52	0.08	0.01
Wind power density performances												
Lalibela	0.988	0.0001	0.002	0.987	0.000008	0.06	0.999995	0.00000004	0.00002	0.993	0.00004	0.002
Amdework	0.995	0.000001	0.0001	0.994	0.000004	0.004	0.99994	0.00000008	0.00002	0.995	0.00003	0.0017

Ambamaryam	0.994	0.000001	0.000002	0.988	0.000009	0.007	0.999997	0.00000002	0.00001	0.996	0.00003	0.0017
Wegeltena	0.997	0.000001	0.0002	0.989	0.0006	0.007	0.99977	0.0000004	0.002	0.973	0.0004	0.004

Table 14: Narration of artificial intelligence and empirical models with determinant features

Aspect	AI Models	Empirical Models
Approach	Data-driven, learn patterns from data	Based on theoretical assumptions, mathematical formulations
Model Development	Requires large amounts of training data	Relies on domain knowledge and expert input
Flexibility	Can adapt to complex, non-linear relationships	Limited by underlying assumptions and simplifications
Interpretability	Often treated as "black boxes"	Model structure and parameters are interpretable
Generalization	Can generalize well to unseen data (if trained properly)	May not generalize well outside of the defined scope
Scalability	Highly scalable with increasing data and computing power	Limited scalability due to theoretical constraints
Adaptability	Can adapt to new data and scenarios through retraining	Static models, require manual updates or reformulations
Uncertainty Handling	Can quantify uncertainties through techniques like Bayesian methods	Uncertainties may be difficult to quantify or incorporate
Domain Knowledge	Learns patterns directly from data, no explicit domain knowledge required	Requires substantial domain knowledge for model formulation

Applications	Computer vision, natural language processing, recommendation systems, etc.	Physics-based simulations, engineering models, econometric models, etc.
Examples	Neural Networks, ANN, LSTM, Random Forests, Gradient Boosting, etc.	Weibull Distribution, Wind Speed Extrapolation, Fluid Dynamics Models, etc.

As we have seen the performance of the different models, the LSTM model is the best one of the rest. Whereas when we compare artificial intelligence with empirical models, the artificial intelligence models are too smart because of the above reasons, so I have selected the artificial intelligence, especially the LSTM, part of recurrent neural network algorithm, to predict wind energy with advancement in the Wello highlands upper basin of Tekeze and Abay to get efficient energy production.

5. Conclusion and Recommendation

5.1. Conclusion

The study analised, how well empirical and artificial models especially LSTM, ANN, XGBoost, and Gradient Boost improved wind speed prediction at Wello Highlands upper basin of Abay and Tekeze in Ethiopia. The wind power production may vary in speed, and there is a noticeable increase in wind power density when the frequency distribution is assessed at 10 and 50 meters. The wind in the study area has a seasonal trend; January, March, April, May, and October are when reasonably high wind power density is reported. The water level in Ethiopia's hydropower reservoirs will be low throughout these months. Owing to these innate characteristics, wind energy is an excellent addition to hydropower.

This research also demonstrated the superior capability of artificial intelligence (AI) techniques over empirical models for predicting wind energy potential in Ethiopia's Wello Highlands upper basin of Abay and Tekeze. The long short-term memory (LSTM) neural network architecture provided the highest accuracy in modeling the wind speed time series data, explaining over 97% of the variance across the study sites. The research also highlighted the gradient-boosting machine's excellence in predicting wind power density, achieving over 99.9% accuracy. The explicit modeling of both short- and long-term temporal dependencies in meteorological data enabled the LSTM model to significantly outperform other methods without native sequence understanding.

The study provided evidence that artificial intelligence approaches like LSTM networks are uniquely suited to capturing complex wind patterns critical for positioning wind turbines and planning energy infrastructure. The integration of accurate artificial intelligence-based wind energy forecasts will be pivotal to expanding Ethiopia's wind power generation capacity to meet national renewable energy targets and rising electricity demands in a sustainable manner.

5.2. Recommendation

Recommendations for Future Researchers:

1. Future researchers should consider expanding the scope of the study to include a broader range of geographical locations and sites in Ethiopia in order to provide a more comprehensive and effective understanding of wind energy potentials in the country to meet our demands.
2. It is recommended that future researchers consider conducting studies that not only assess wind speed and potential but also cover grid connection studies, economic analysis, and the design of wind turbines to provide a more holistic view of wind energy potential and implementation.
3. Due to the dynamic nature of technology, future researchers should keep abreast of advancements in artificial intelligence and empirical modeling in the context of wind energy prediction to ensure the most up-to-date and accurate methodologies are used in similar studies.

Recommendations for Policy Makers:

1. Policymakers should consider utilizing the findings of this study to inform the development and implementation of policies aimed at promoting and harnessing wind energy in Ethiopia with sufficient and reliable data.
2. Due to the identified significance of the study in contributing to the general knowledge of wind energy potential, policymakers should incentivize and support further research in this area to increase understanding and implementation of sustainable energy sources in the country because wind energy is complementary with hydropower and solar energies that meet the SDGs, green energy, and also to support the dominated alternative hydropower energy in the country.
3. Policymakers should also engage with researchers and stakeholders to ensure the findings of this study are incorporated into national energy plans and strategies, with a focus on expanding wind energy infrastructure to meet the growing energy demand in the country.

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Appendices

	Wegeltena	Lalibela	Amdework	Ambamaryam
Jan	2.510323	2.51173	2.59718	2.53287
Feb	2.640881	2.59794	2.73901	2.68389
Mar	2.535954	2.69754	2.82339	2.70684
Apr	2.700458	3.00438	3.06432	2.72413
May	2.768226	3.15226	3.0296	2.75798
Jun	2.595167	3.11638	2.78083	2.70329
Jul	2.068226	2.48278	2.13952	2.08097
Aug	1.817944	2.29802	1.93718	1.85694
Sep	2.006333	2.66158	2.36688	2.01233
Oct	2.433387	3.12056	3.09645	2.49766
Nov	2.575303	2.91663	3.01104	2.5913
Dec	2.517742	2.68724	2.83923	2.52488
Avg.	2.430829	2.770586	2.702052	2.472757

Months	10 m	50 m	100 m
1	2.511733871	4.070658067	5.011567938
2	2.597938732	4.210366543	5.183569248
3	2.697540323	4.371786519	5.382300549
4	3.004375	4.869060163	5.994516218
5	3.152258065	5.108727827	6.289581723
6	3.116375	5.050573702	6.217985597
7	2.482782258	4.023737445	4.953801876
8	2.298024194	3.724308069	4.585161072
9	2.661583333	4.313512587	5.310556923
10	3.120564516	5.057363468	6.22634478

11	2.916625	4.726847546	5.819431949
12	2.687235023	4.355085167	5.361738773

A. Amdework

Months	10 m	50 m	100 m
1	2.597177419	4.211240225	5.184644876
2	2.7390117	4.343583592	5.347578673
3	2.823387097	4.623674456	5.692410976
4	3.064318548	5.071706769	6.244003455
5	3.029596774	4.965858452	6.113688891
6	2.780833333	4.555834512	5.608890207
7	2.139516129	3.451247037	4.248983508
8	1.937177419	3.133503588	3.857795436
9	2.366875	3.843361796	4.731733404
10	3.096451613	5.137285364	6.324740176
11	3.011041667	4.922482744	6.06028713
12	2.839233871	4.691122851	5.77544969

A. **Ambamaryam**

Months	**10 m**	**50 m**	**100 m**
1	**2.532865423**	**4.104905057**	**5.053730928**
2	**2.683886494**	**4.349658352**	**5.35505758**
3	**2.706841398**	**4.386860368**	**5.400858634**
4	**2.724125**	**4.414871151**	**5.435343954**

5	**2.757983871**	**4.469744754**	**5.502901283**
6	**2.703291667**	**4.381107472**	**5.393775989**
7	**2.080967742**	**3.372534098**	**4.152076514**
8	**1.856944444**	**3.009469264**	**3.705091271**
9	**2.012333333**	**3.261301291**	**4.015132865**
10	**2.49766129**	**4.047851246**	**4.983489448**
11	**2.591302766**	**4.199611922**	**5.170328756**
12	**2.524879032**	**4.091961859**	**5.037795983**

Table: Average Wind power density at 10 m, 50 m and 100 m

Months	10 m	30 m	50 m
1	9.728899423	41.41300241	77.27939505
2	11.32716915	48.21635652	89.97490273
3	10.02996425	42.69454494	79.67083798
4	12.11121065	51.5537857	96.20276579
5	13.04606851	55.53319477	103.6286057
6	10.74906969	45.7555608	85.38289554
7	5.440877828	23.16018254	43.21842881
8	3.695015762	15.72857216	29.35055347
9	4.966888166	21.14255093	39.45339509
10	8.861530127	37.72087186	70.38963583
11	10.50412784	44.71291692	83.43725326
12	9.815417035	41.78128189	77.96662886

A. Lalibela

Table: Average Wind power density at 10 m, 30 m and 50 m

Months	10 m	50 m	100 m
1	9.745317259	41.4828882	77.40980655
2	10.78355182	45.90234087	85.65679684
3	12.07199234	51.38684514	95.89124369
4	16.67775287	70.99218418	132.4761
5	19.26373118	81.99991705	153.0172558
6	18.61333745	79.23138631	147.8509948
7	9.412197153	40.06489597	74.76373949

A. Wegeltena

Months	V_{av}	STD	K	c(m/s)
1	2.706912	0.73231	4.136263	2.985195
2	2.897027	0.99278	3.199617	3.238483
3	3.113364	0.861419	4.036498	3.438299
4	3.255238	0.984806	3.663414	3.614434
5	3.535484	1.132705	3.442266	3.938323
6	3.308571	0.914948	4.038806	3.65376
7	2.615668	0.667597	4.406279	2.87374
8	2.38341	0.658694	4.041545	2.631972
9	2.942058	0.820551	4.001627	3.250734
10	3.701382	0.959156	4.334225	4.070614
11	3.12	0.942817	3.667952	3.464044
12	2.806354	0.82652	3.771776	3.1111
Average	3.032123	0.874525	3.895022	3.355892

B. Lalibela

Months	V_{av}	STD	k	c(m/s)
1	1.870046	0.619923	1.9122	1.69
2	2.049895	0.588248	2.05	1.85
3	2.113364	0.668769	1.99	1.90

4	2.290952	0.744519	1.99	2.05
5	2.054608	0.816021	1.89	1.85
6	1.877143	0.816629	1.62	1.65
7	1.158525	0.638228	1.97	1.05
8	1.256388	0.592511	2.12	1.13
9	1.368784	0.662306	1.89	1.22
10	1.743164	0.662802	2.05	1.56
11	1.722857	0.581096	2.12	1.55
12	1.752074	0.597373	2.05	1.57
Average	**1.77148**	**0.6657**	**1.97102**	**1.58917**

C. Amdework

Months	V_{av}	STD	k	c(m/s)
1	1.409923	0.518579	1.754	0.759
2	2.187358	0.57039	1.722	1.718
3	1.69312	0.498243	1.890	1.303
4	2.210614	0.511267	1.764	1.727
5	1.711058	0.584861	1.880	1.383
6	1.638632	0.59679	1.937	1.299
7	1.133359	0.584334	1.959	0.997
8	0.979976	0.497555	1.732	.0.925

9	1.135913	0.47687	1.727	1.038
10	1.067628	0.479052	1.764	0.977
11	0.995706	0.450529	1.849	0.995
12	0.960104	0.424207	1.853	0.960
Average	1.426949	0.516056	1.81925	1.196

D. Ambamaryam

Table: Ambamariam

Months	V_{av}	STD	k	C(m/s)
1	1.806452	0.473779	1.682	1.806
2	1.816854	0.428394	1.684	1.817
3	1.869124	0.437753	1.666	1.869
4	1.938095	0.53505	1.563	1.938
5	1.754839	0.468946	1.586	1.755
6	1.673333	0.411956	1.687	1.673
7	1.364055	0.415375	1.692	1.364
8	1.340092	0.370308	2.058	1.170
9	1.666667	0.393806	2.068	1.202
10	2.014747	0.534381	2.137	1.392
11	1.86	0.526671	2.067	1.235

12	1.703226	0.416587	2.067	1.235
Average	1.733957	0.451084	1.82975	1.538